

# Computer Vision

ACTL3143 & ACTL5111 Deep Learning for Actuaries  
Patrick Laub



# Lecture Outline

- **Images**
- Convolutional Layers
- Convolutional Layer Options
- Convolutional Neural Networks
- Demo: Character Recognition
- Demo: Character Recognition II
- Error Analysis
- Hyperparameter tuning
- Leveraging Solutions From Benchmark Problems
- Transfer Learning



# Shapes of data

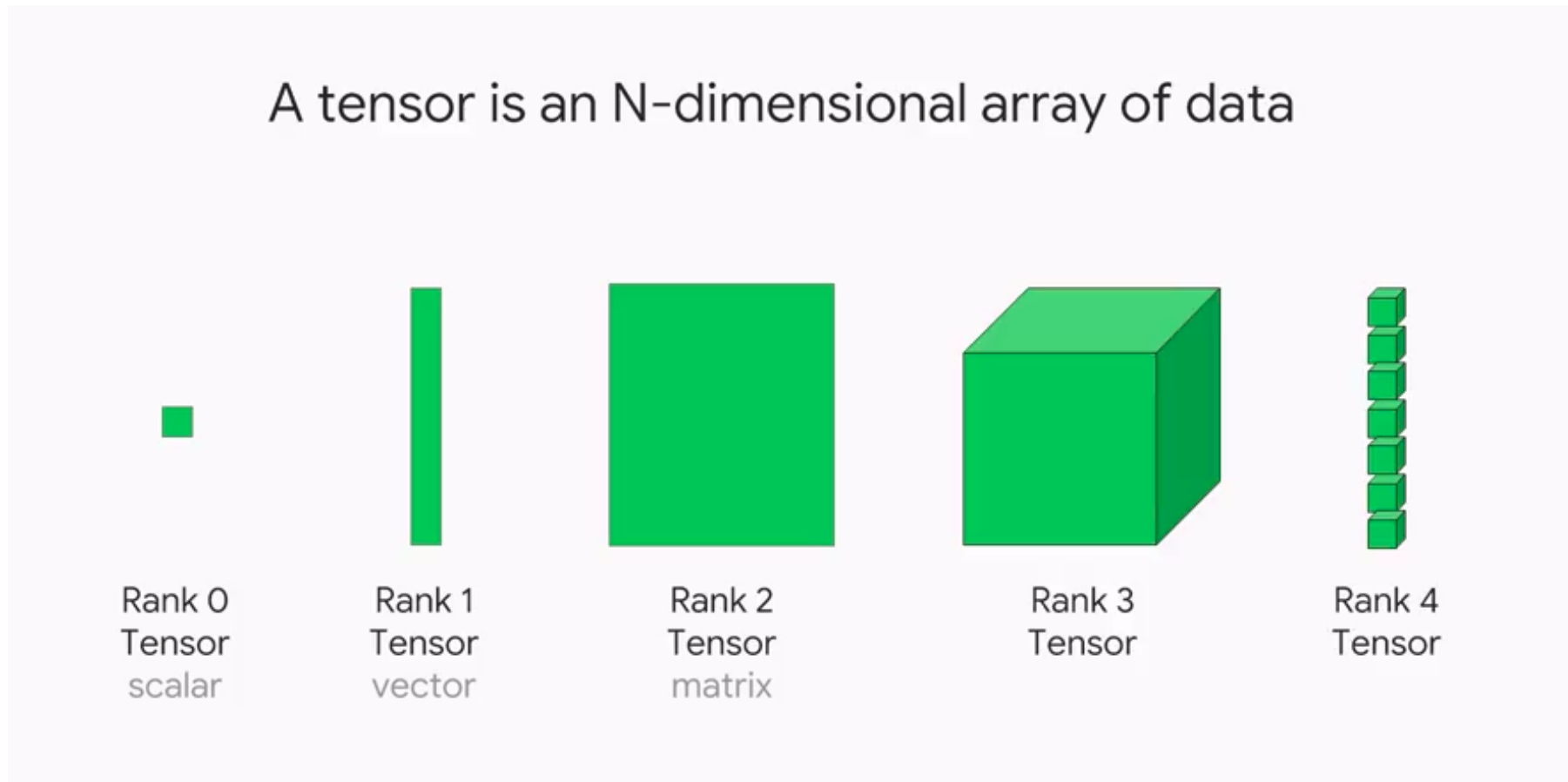
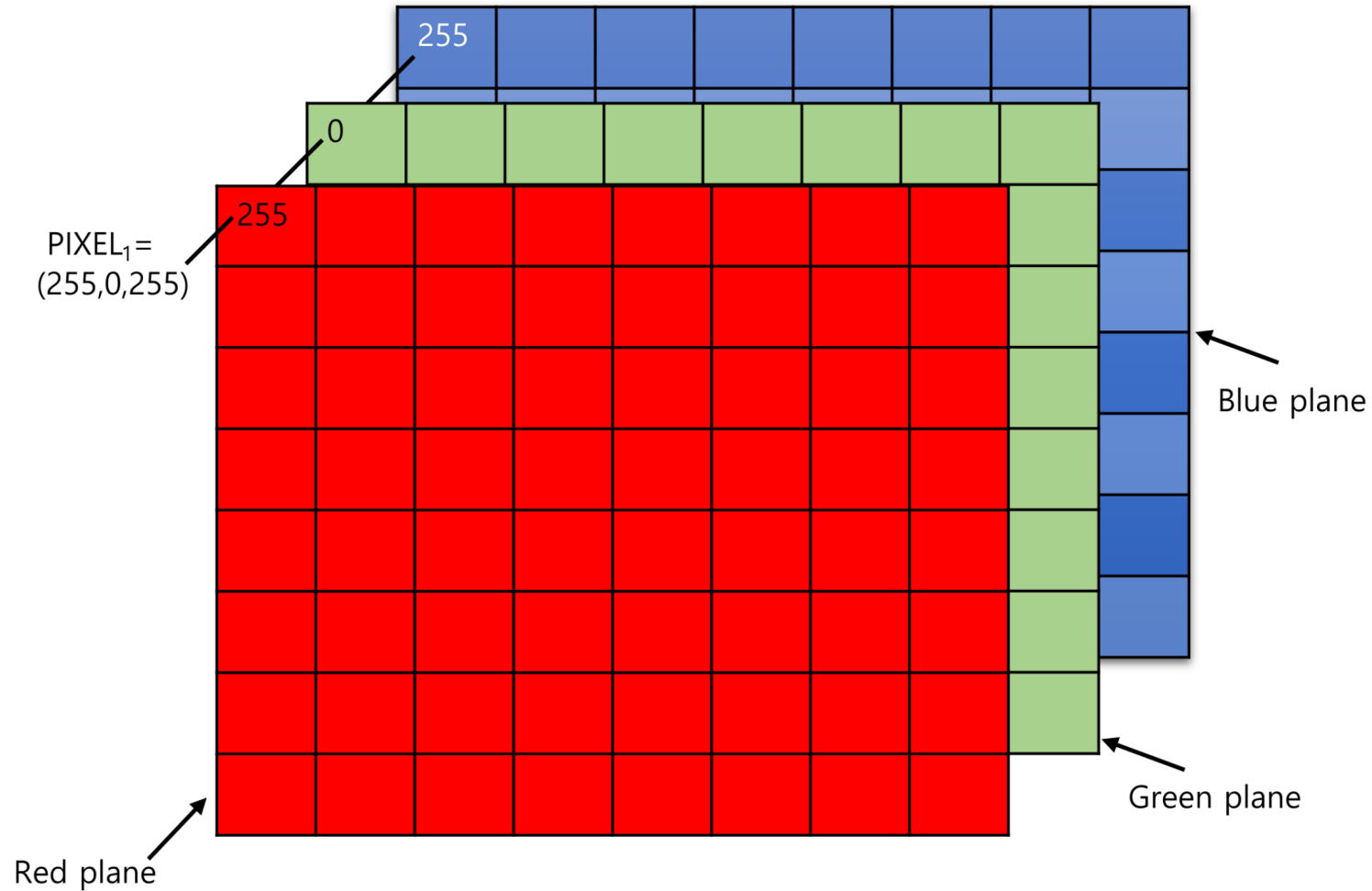


Illustration of tensors of different rank.



Source: Paras Patidar (2019), [Tensors — Representation of Data In Neural Networks](#), Medium article.

# Shapes of photos



A photo is a rank 3 tensor.



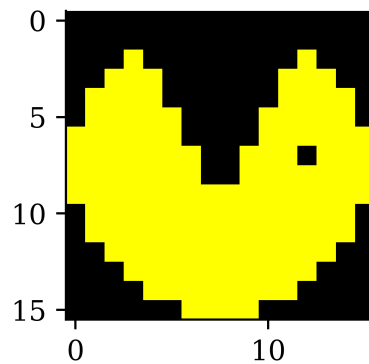
Source: Kim et al (2021), [Data Hiding Method for Color AMBTC Compressed Images Using Color Difference](#), Applied Sciences.



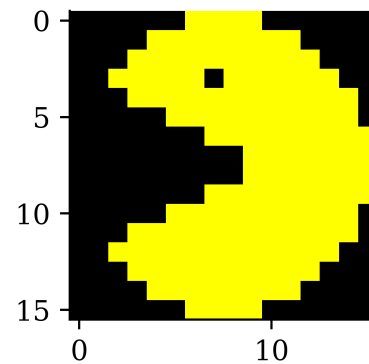
# How we see them

```
1 from matplotlib.pyplot import imshow
```

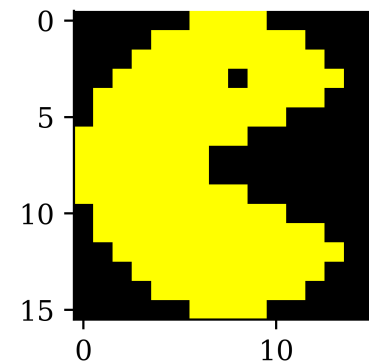
```
1 imshow(img1);
```



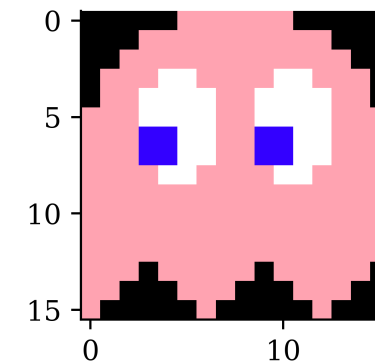
```
1 imshow(img2);
```



```
1 imshow(img3);
```



```
1 imshow(img4);
```



# Why is 255 special?

Each pixel's colour intensity is stored in one byte.

One byte is 8 bits, so in binary that is 00000000 to 11111111.

The largest *unsigned* number this can be is  $2^8 - 1 = 255$ .

```
1 np.array([0, 1, 255, 256]).astype(np.uint8)
```

```
array([ 0,  1, 255,  0], dtype=uint8)
```

If you had *signed* numbers, this would go from -128 to 127.

```
1 np.array([-128, 1, 127, 128]).astype(np.int8)
```

```
array([-128,  1, 127, -128], dtype=int8)
```

Alternatively, *hexidecimal* numbers are used. E.g. 10100001 is split into 1010 0001, and 1010=A, 0001=1, so combined it is 0xA1.



# Image editing with kernels

Take a look at <https://setosa.io/ev/image-kernels/>.

1 <sub>x1</sub>	1 <sub>x0</sub>	1 <sub>x1</sub>	0	0
0 <sub>x0</sub>	1 <sub>x1</sub>	1 <sub>x0</sub>	1	0
0 <sub>x1</sub>	0 <sub>x0</sub>	1 <sub>x1</sub>	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved  
Feature

An example of an image kernel in action.

Source: [Stanford's deep learning tutorial](#) via [Stack Exchange](#).





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# ‘Convolution’ not ‘complicated’

Say  $X_1, X_2 \sim f_X$  are i.i.d., and we look at  $S = X_1 + X_2$ .

The density for  $S$  is then

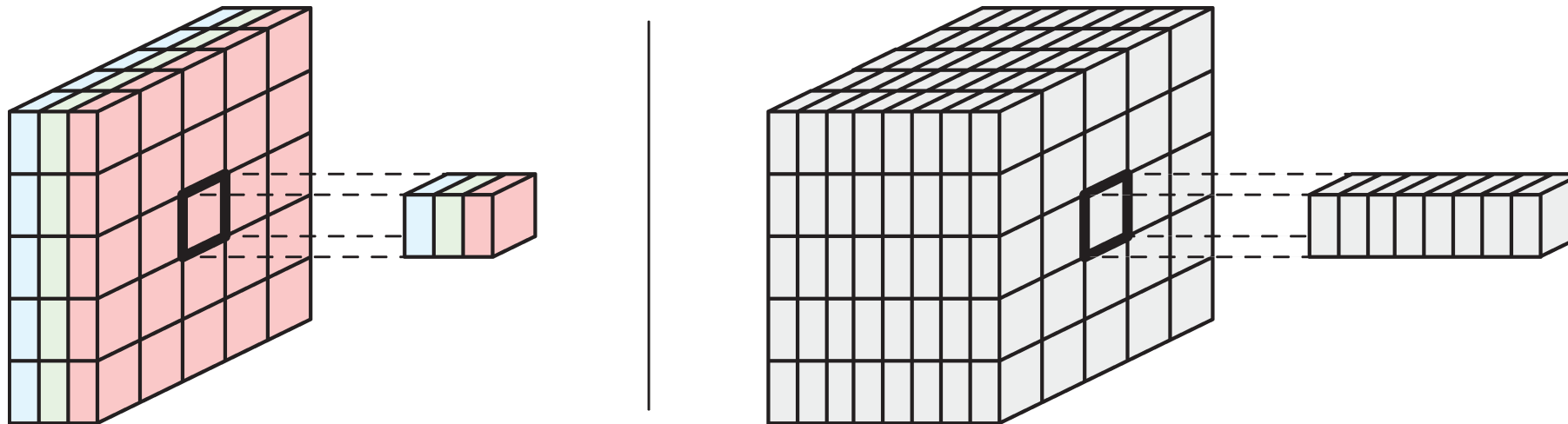
$$f_S(s) = \int_{x_1=-\infty}^{\infty} f_X(x_1) f_X(s - x_1) ds.$$

This is the *convolution* operation,  $f_S = f_X \star f_X$ .



# Images are rank 3 tensors

Height, width, and number of channels.



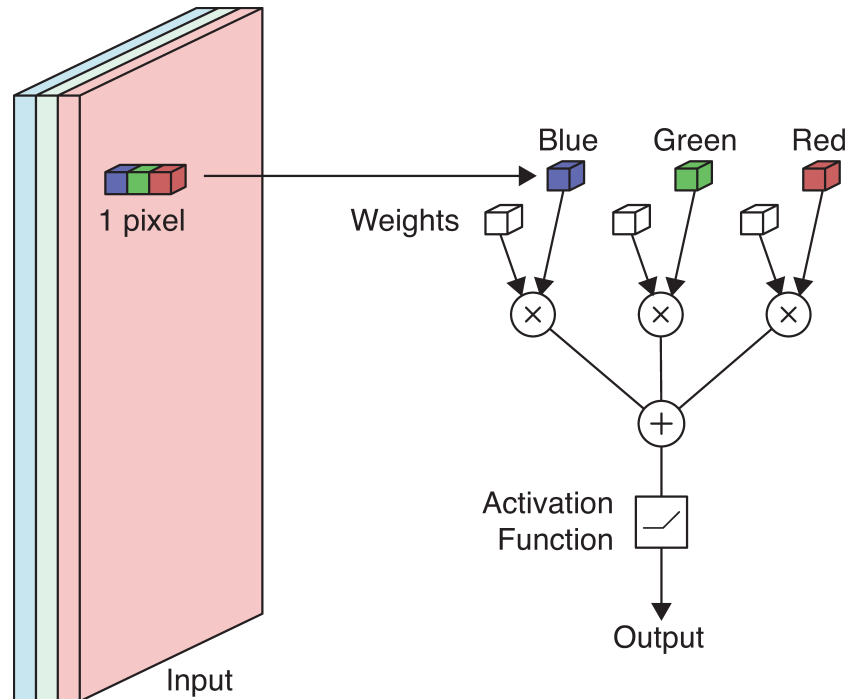
Examples of rank 3 tensors.

Grayscale image has 1 channel. RGB image has 3 channels.

Example: Yellow = Red + Green.



# Example: Detecting yellow



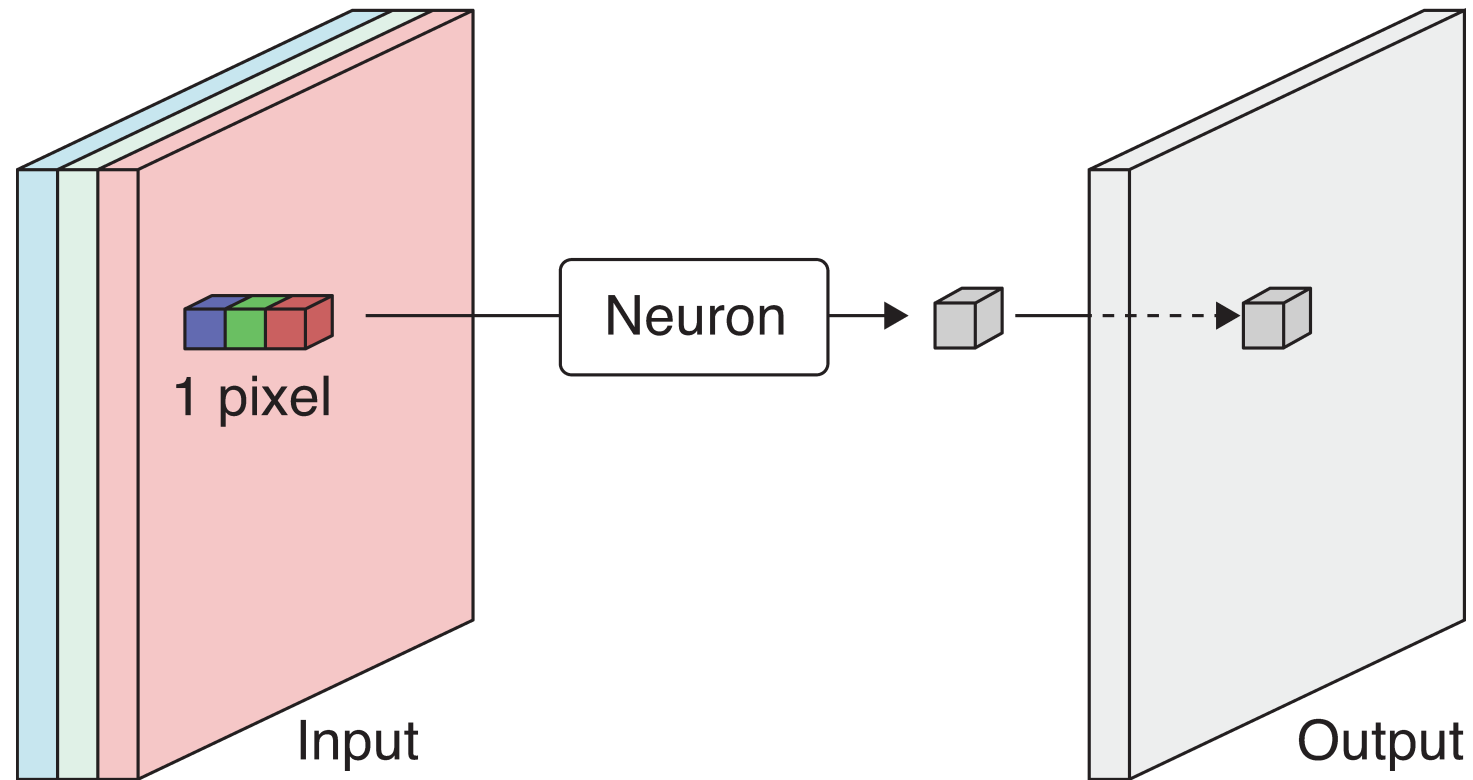
Apply a neuron to each pixel in the image.

If red/green  $\nearrow$  or blue  $\searrow$  then yellowness  $\nearrow$ .

Set RGB weights to 1, 1, -1.

Applying a neuron to an image pixel.

# Example: Detecting yellow II



Scan the 3-channel input (colour image) with the neuron to produce a 1-channel output (grayscale image).

The output is produced by *sweeping* the neuron over the input. This is called **convolution**.

Source: Glassner (2021), *Deep Learning: A Visual Approach*, Chapter 16.



# Example: Detecting yellow III



The more yellow the pixel in the colour image (left), the more white it is in the grayscale image.

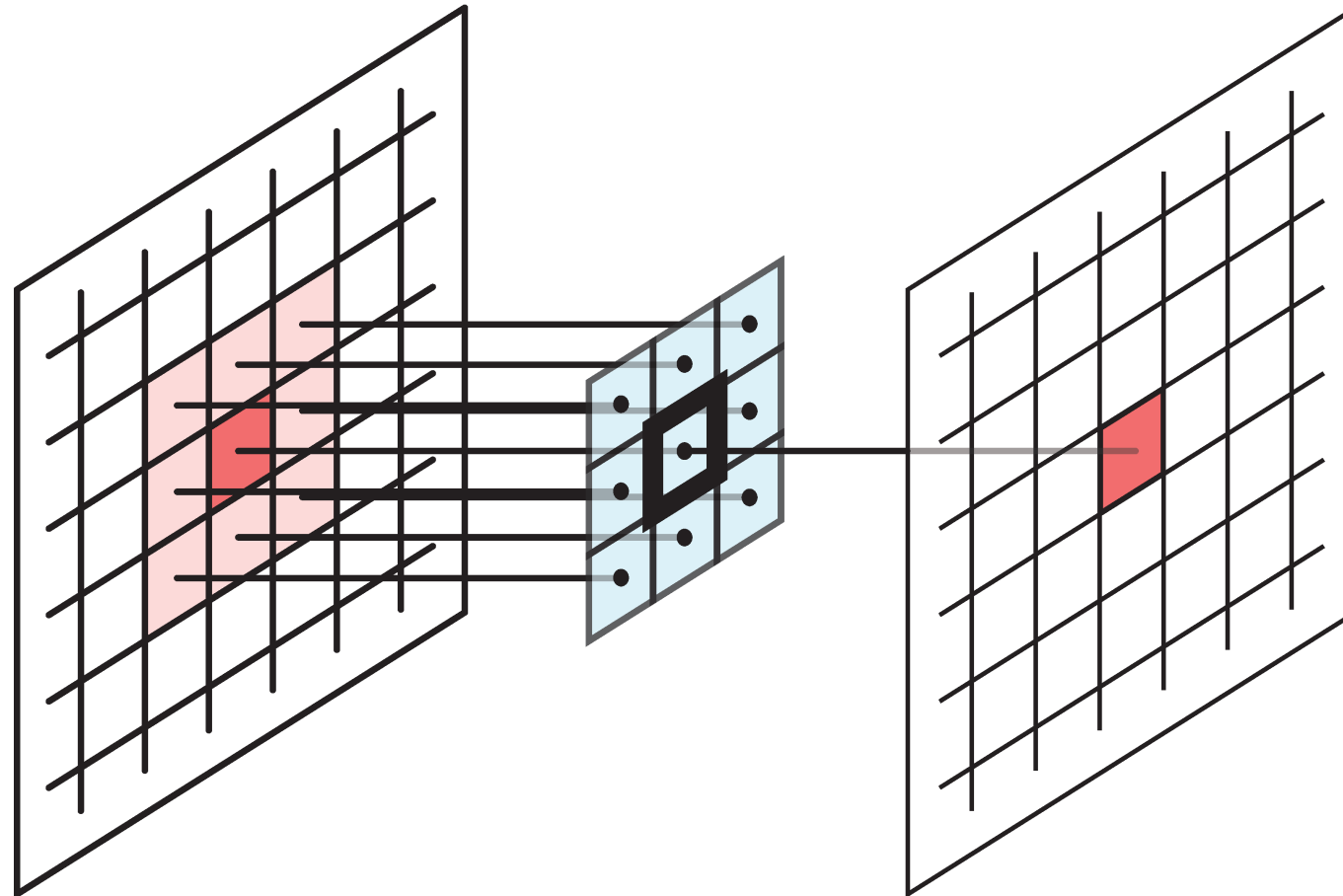
The neuron or its weights is called a **filter**. We *convolve* the image with a filter, i.e. a **convolutional filter**.

# Terminology

- The same neuron is used to sweep over the image, so we can store the weights in some shared memory and process the pixels in parallel. We say that the neurons are *weight sharing*.
- In the previous example, the neuron only takes one pixel as input. Usually a larger filter containing a *block of weights* is used to process not only a pixel but also its neighboring pixels all at once.
- The weights are called the filter **kernels**.
- The cluster of pixels that forms the input of a filter is called its *footprint*.



# Spatial filter



Example 3x3 filter

When a filter's footprint is  $> 1$  pixel, it is a **spatial filter**.

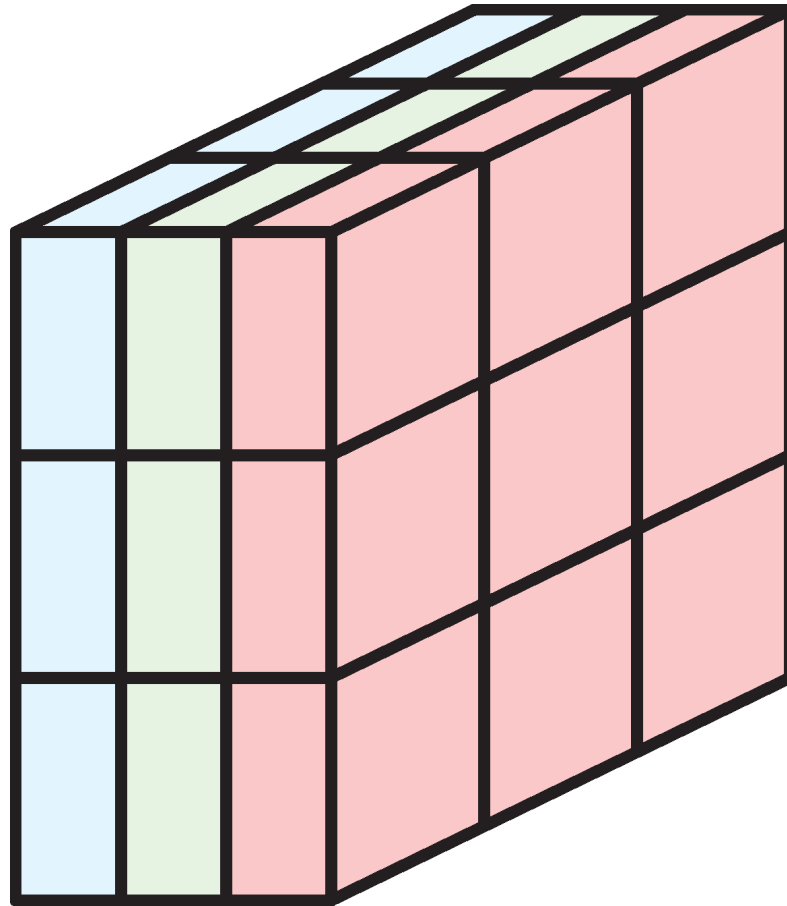
Source: Glassner (2021), *Deep Learning: A Visual Approach*, Chapter 16.





# Multidimensional convolution

Need # Channels in Input = # Channels in Filter.

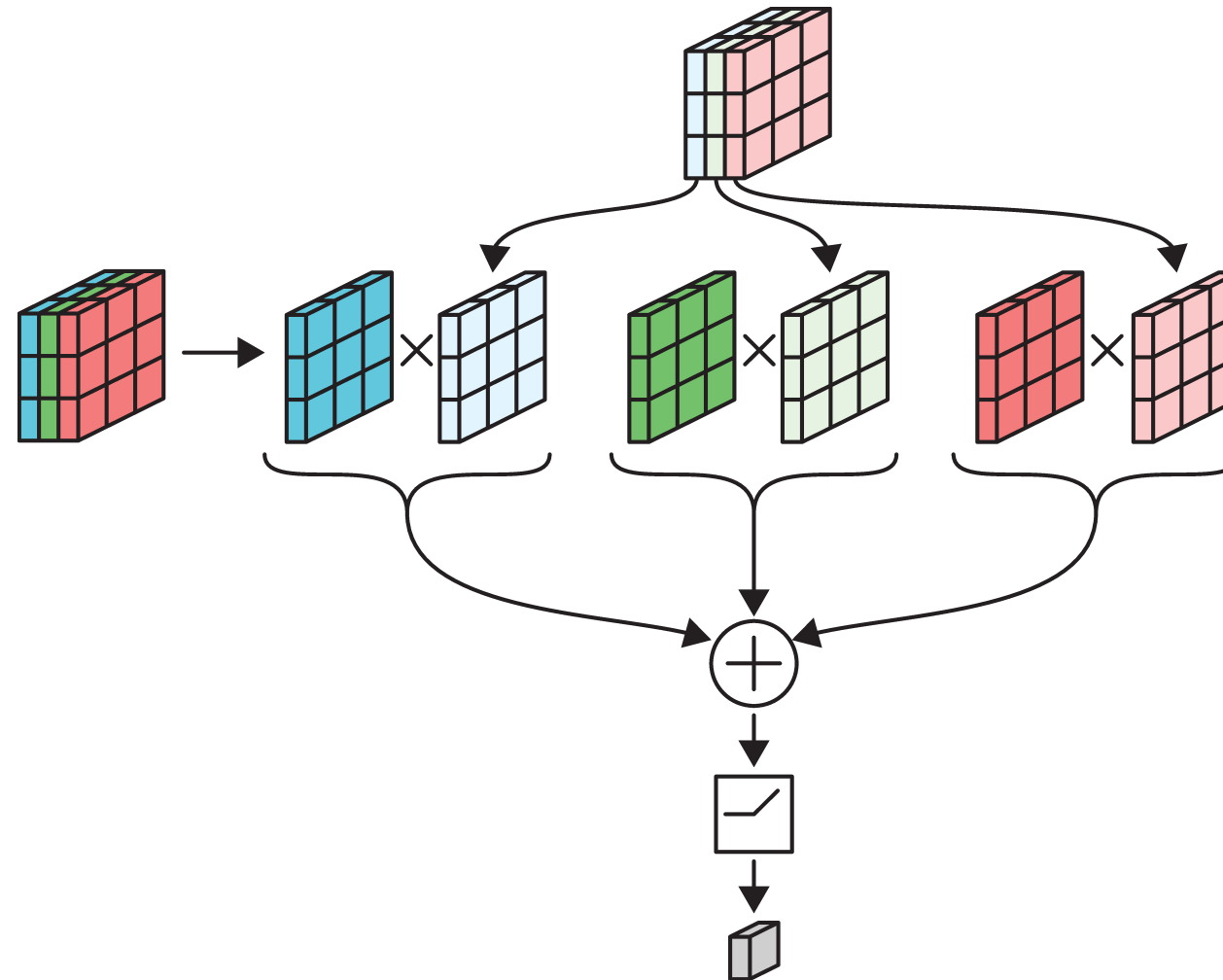


Example: a 3x3 filter with 3 channels, containing 27 weights.

Source: Glassner (2021), *Deep Learning: A Visual Approach*, Chapter 16.



# Example: 3x3 filter over RGB input

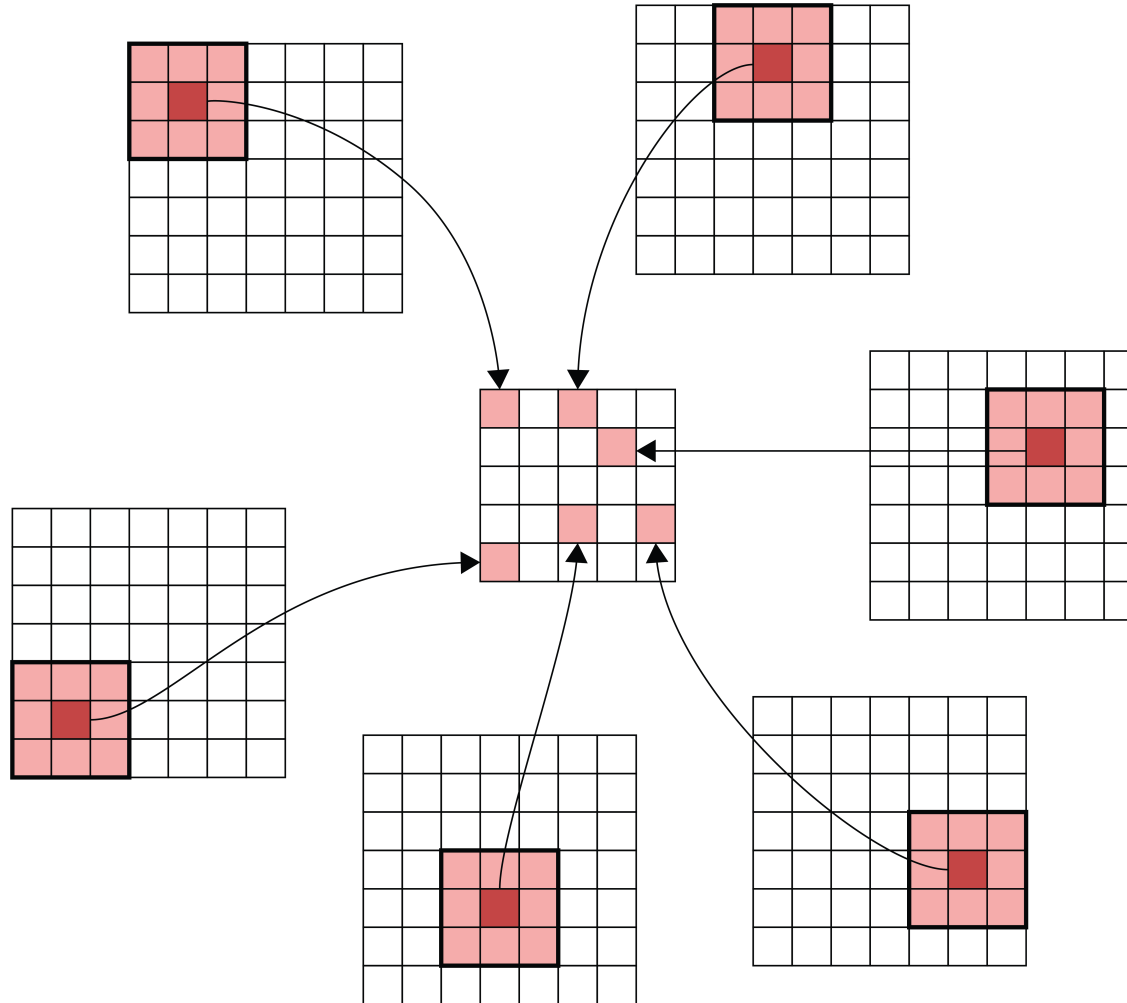


Each channel is multiplied separately & then added together.

Source: Glassner (2021), *Deep Learning: A Visual Approach*, Chapter 16.



# Input-output relationship



Matching the original image footprints against the output location.

Source: Glassner (2021), *Deep Learning: A Visual Approach*, Chapter 16.

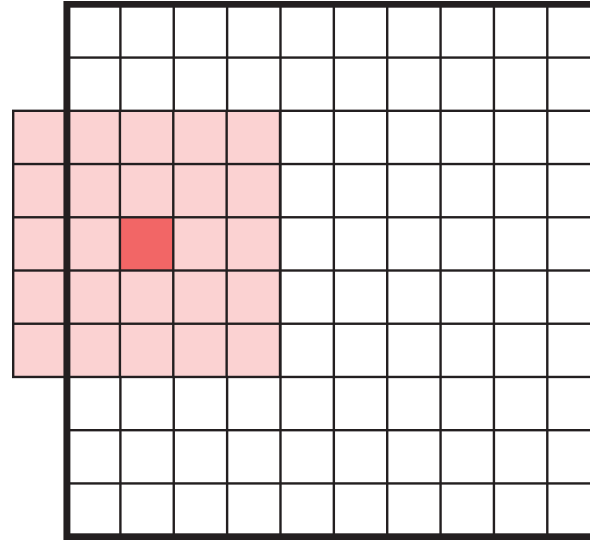


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# Padding



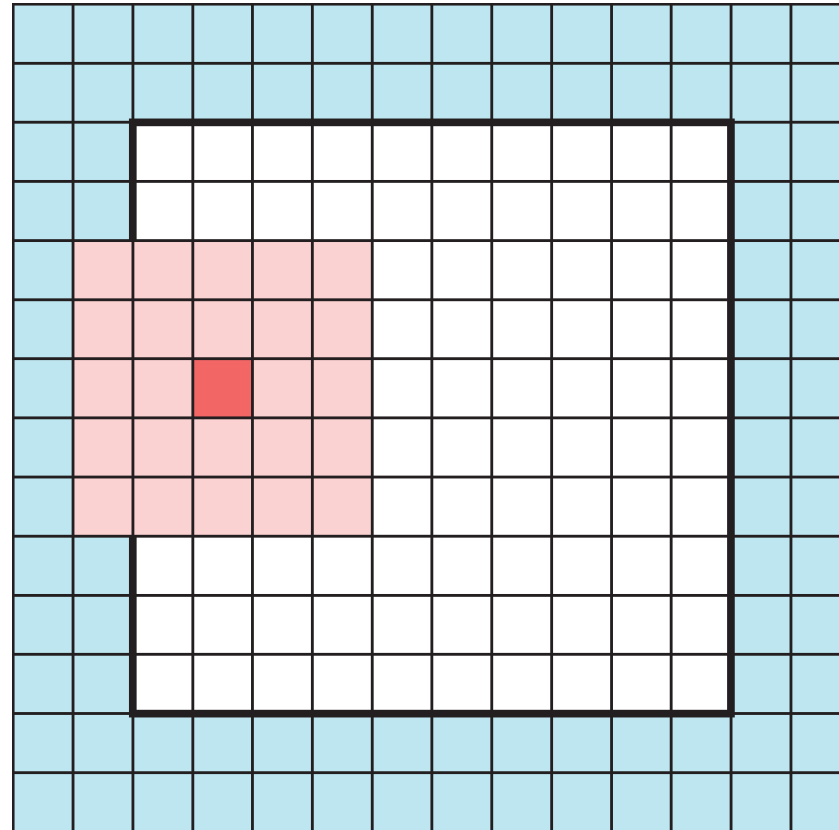
What happens when filters go off the edge of the input?

- How to avoid the filter's receptive field falling off the side of the input.
- If we only scan the filter over places of the input where the filter can fit perfectly, it will lead to loss of information, especially after many filters.



# Padding

Add a border of extra elements around the input, called **padding**.  
Normally we place zeros in all the new elements, called **zero padding**.



Padded values can be added to the outside of the input.

Source: Glassner (2021), *Deep Learning: A Visual Approach*, Chapter 16.



# Convolution layer

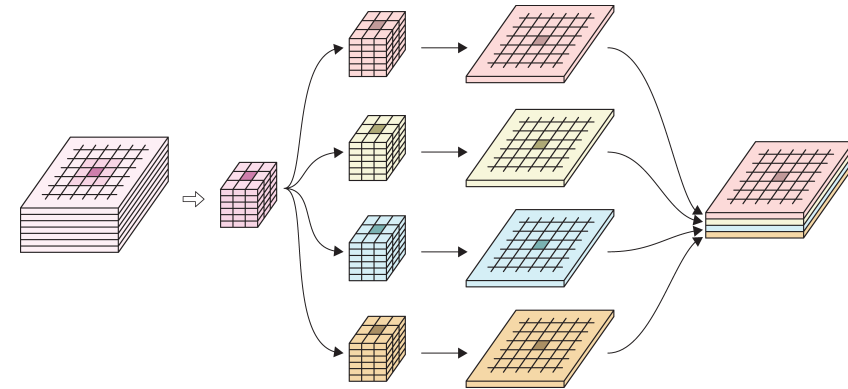
- Multiple filters are bundled together in one layer.
- The filters are applied *simultaneously* and *independently* to the input.
- Filters can have different footprints, but in practice we almost always use the same footprint for every filter in a convolution layer.
- Number of channels in the output will be the same as the number of filters.



# Example

In the image:

- 6-channel input tensor
- input pixels
- four 3x3 filters
- four output tensors
- final output tensor.



Example network highlighting that the number of output channels equals the number of filters.

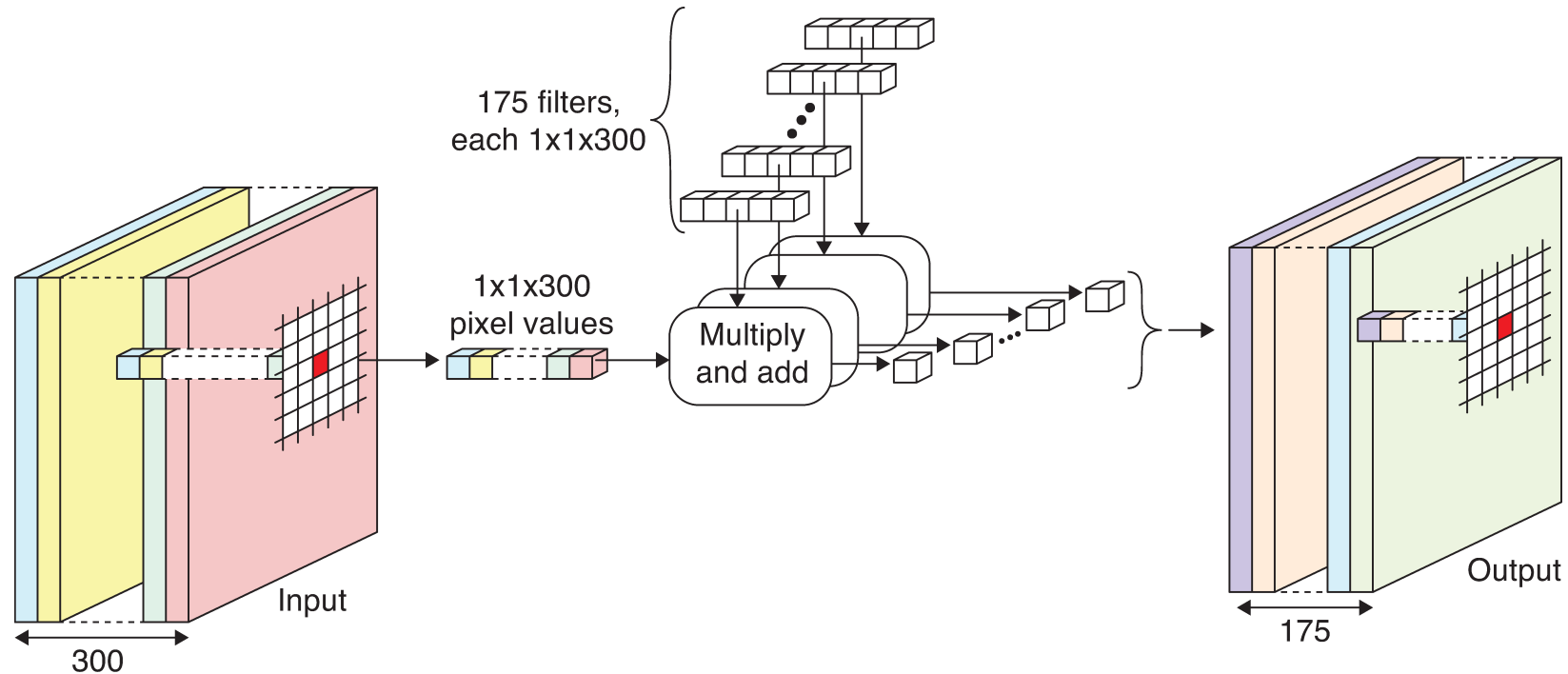


# 1x1 convolution

- Feature reduction: Reduce the number of channels in the input tensor (removing correlated features) by using fewer filters than the number of channels in the input. This is because the number of channels in the output is always the same as number of filters.
- 1x1 convolution: Convolution using 1x1 filters.
- When the channels are correlated, 1x1 convolution is very effective at reducing channels without loss of information.



# Example of 1x1 convolution



Example network with 1x1 convolution.

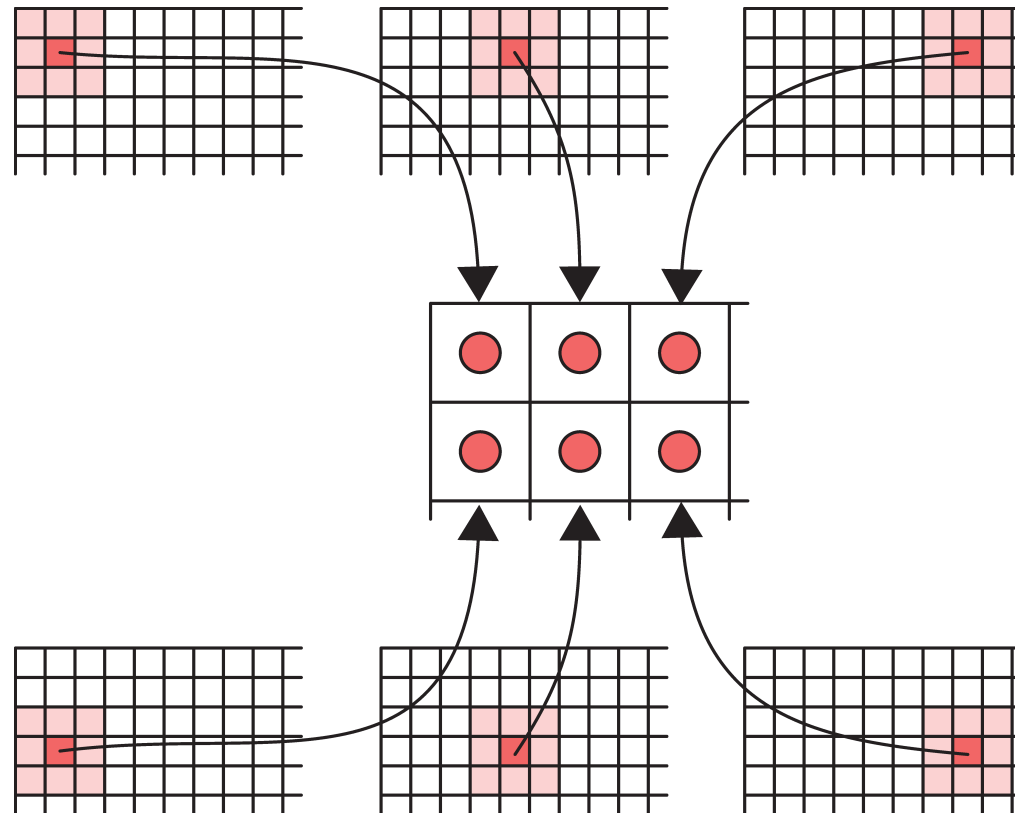
- Input tensor contains 300 channels.
- Use 175 1x1 filters in the convolution layer (300 weights each).
- Each filter produces a 1-channel output.
- Final output tensor has 175 channels.

Source: Glassner (2021), *Deep Learning: A Visual Approach*, Chapter 16.



# Striding

We don't have to go one pixel across/down at a time.



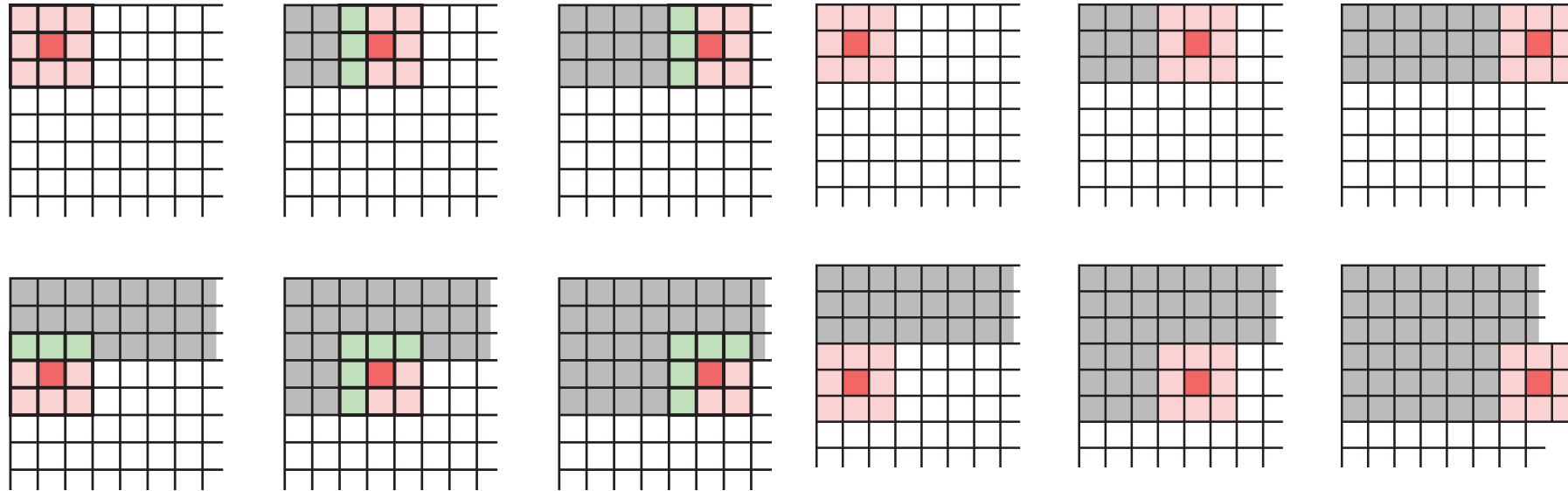
Example: Use a stride of three horizontally and two vertically.

Dimension of output will be smaller than input.

Source: Glassner (2021), *Deep Learning: A Visual Approach*, Chapter 16.



# Choosing strides



When a filter scans the input step by step, it processes the same input elements multiple times. Even with larger strides, this can still happen (left image).

**If** we want to save time, we can choose strides that prevents input elements from being used more than once. Example (right image):  $3 \times 3$  filter, stride 3 in both directions.

# Specifying a convolutional layer

Need to choose:

- number of filters,
- their footprints (e.g. 3x3, 5x5, etc.),
- activation functions,
- padding & striding (optional).

All the filter weights are learned during training.



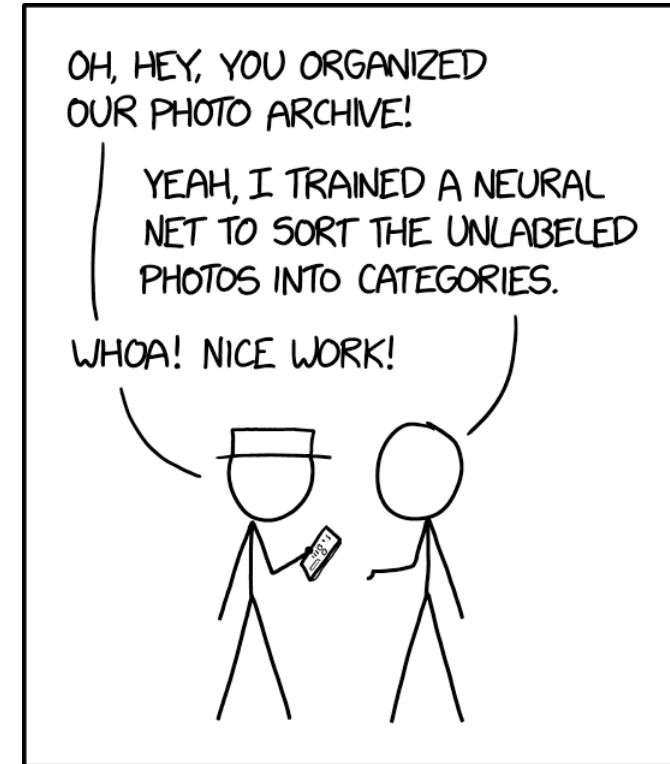
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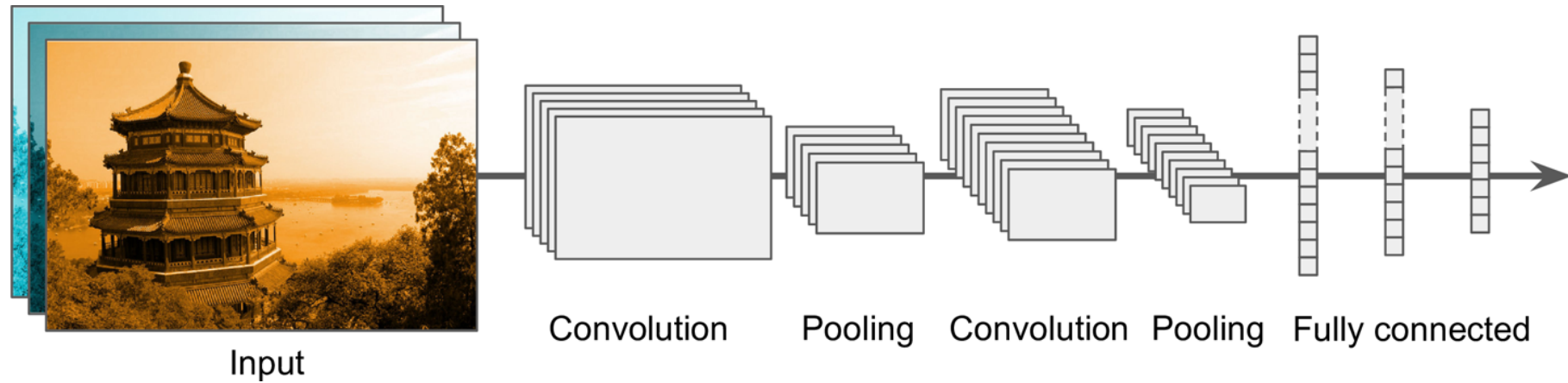
# Definition of CNN

A neural network that uses *convolution layers* is called a *convolutional neural network*.



ENGINEERING TIP:  
WHEN YOU DO A TASK BY HAND,  
YOU CAN TECHNICALLY SAY YOU  
TRAINED A NEURAL NET TO DO IT.

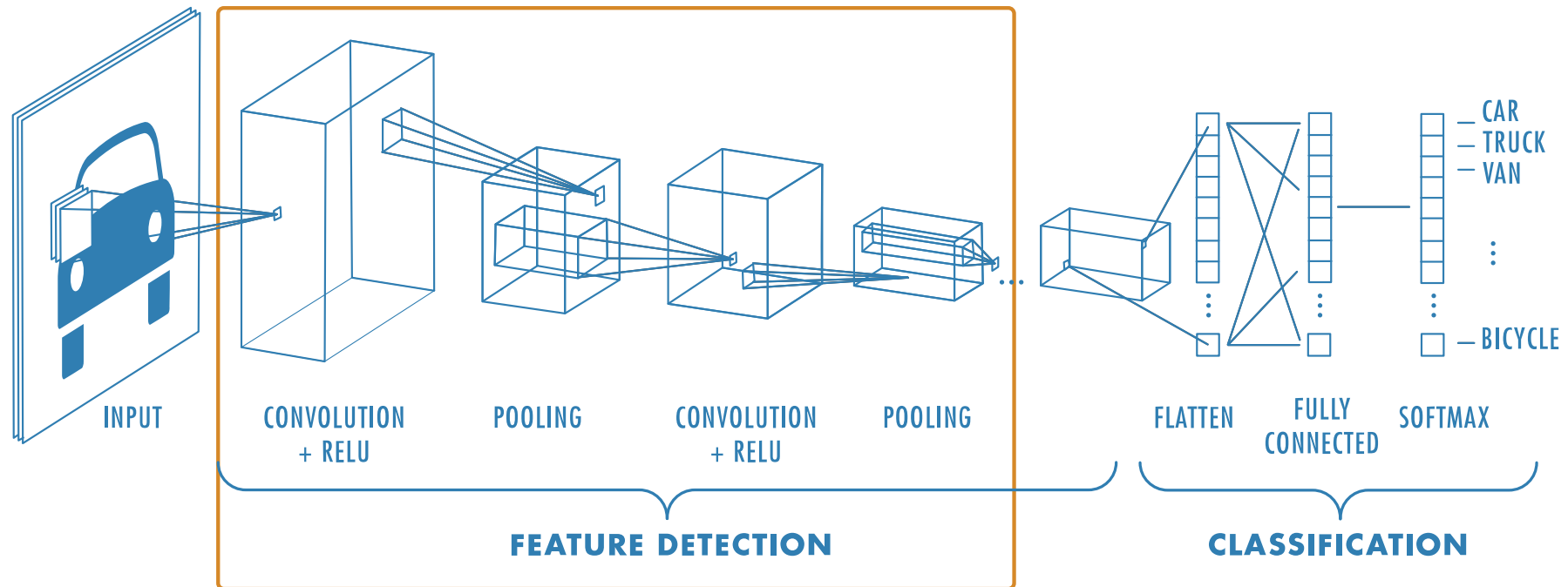
# Architecture



Typical CNN architecture.



# Architecture #2



Source: MathWorks, *Introducing Deep Learning with MATLAB*, Ebook.



# Pooling

**Pooling**, or **downsampling**, is a technique to blur a tensor.

3	2	-3	2
1	6	20	5
4	-13	2	6
-2	3	9	3

(a)

3	2	-3	2
1	6	20	5
4	-13	2	6
-2	3	9	3

(b)

3	6
-2	5

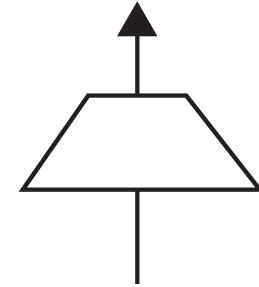
Average

(c)

6	20
4	9

Max

(d)

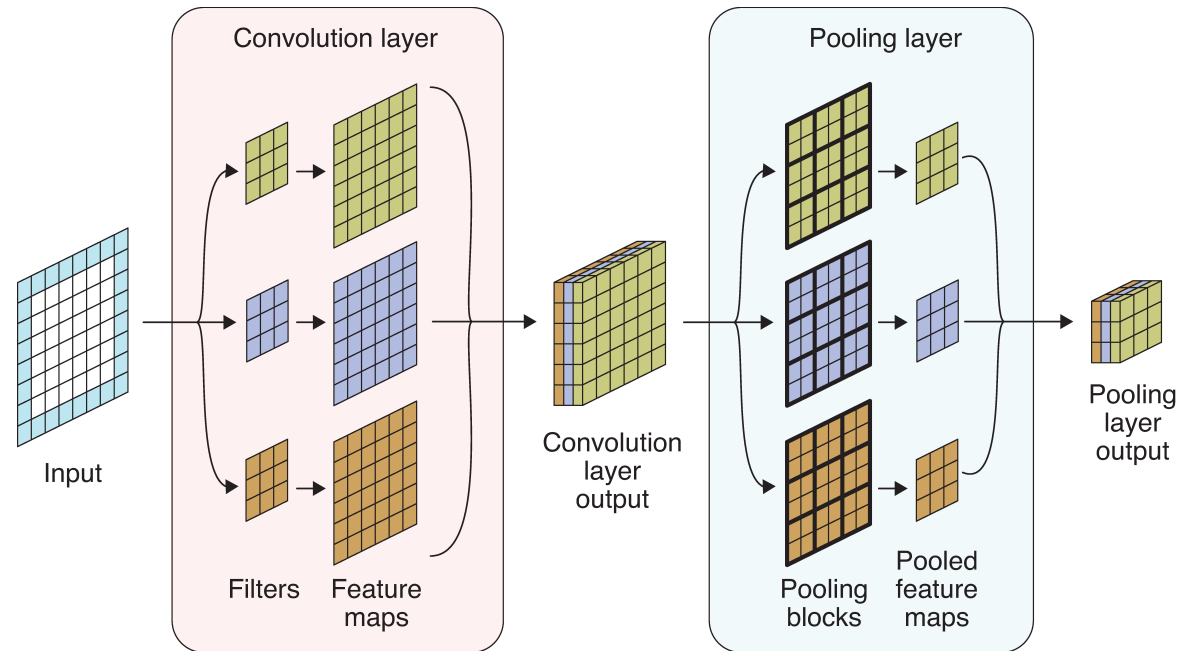


(e)

Illustration of pool operations.

(a): Input tensor (b): Subdivide input tensor into 2x2 blocks (c): Average pooling (d): Max pooling (e): Icon for a pooling layer

# Pooling for multiple channels



Pooling a multichannel input.

- Input tensor: 6x6 with 1 channel, zero padding.
- Convolution layer: Three 3x3 filters.
- Convolution layer output: 6x6 with 3 channels.
- Pooling layer: apply max pooling to each channel.
- Pooling layer output: 3x3, 3 channels.

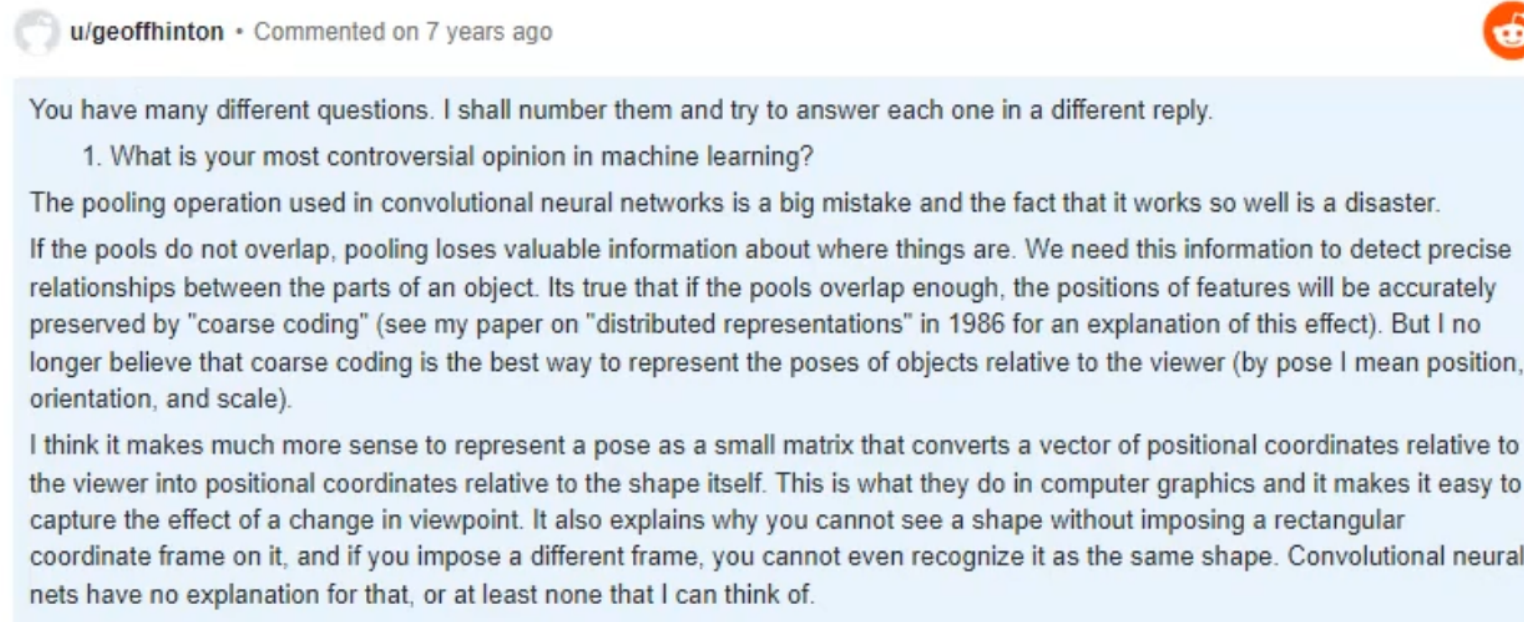
Source: Glassner (2021), *Deep Learning: A Visual Approach*, Chapter 16.



# Why/why not use pooling?

**Why?** Pooling *reduces the size* of tensors, therefore reduces memory usage and execution time (recall that  $1 \times 1$  convolution *reduces the number of channels* in a tensor).

**Why not?**

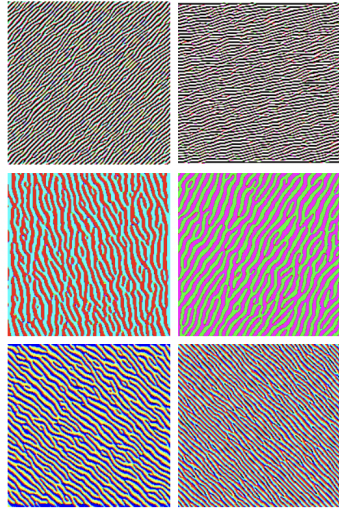


Geoffrey Hinton

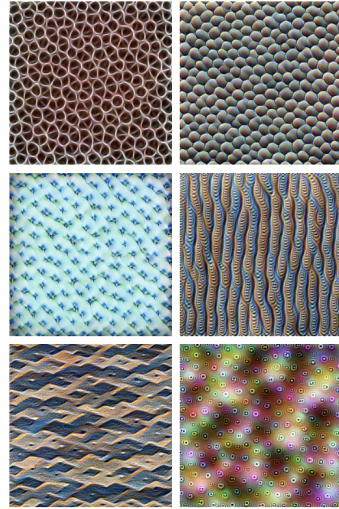
Source: Hinton, [Reddit AMA](#).



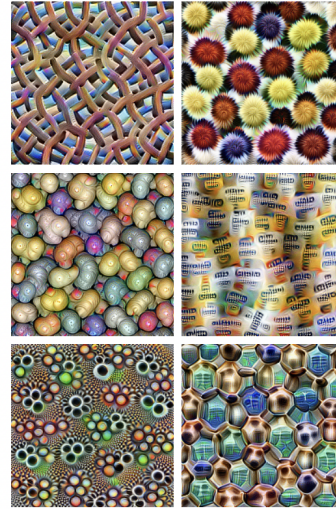
# What do the CNN layers learn?



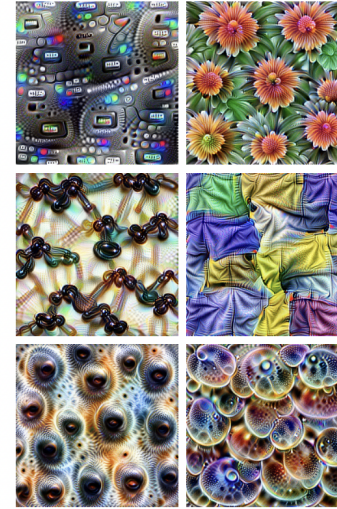
**Edges** (layer conv2d0)



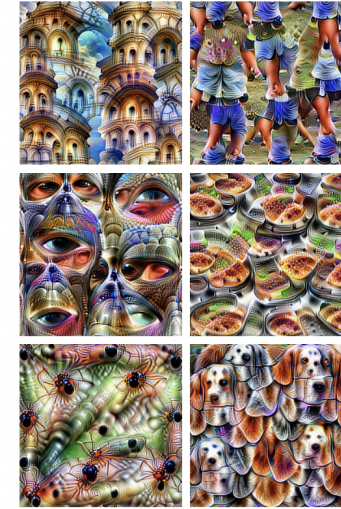
**Textures** (layer mixed3a)



**Patterns** (layer mixed4a)



**Parts** (layers mixed4b & mixed4c)



**Objects** (layers mixed4d & mixed4e)



Source: Distill article, [Feature Visualization](#).

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# MNIST Dataset



The MNIST dataset.

Source: Wikipedia, [MNIST database](#).



# Mandarin Characters Dataset

57 poorly written Mandarin characters ( $57 \times 7 = 399$ ).

人	人	人	人	人	人	人	ren <sup>2</sup>	ren <sup>2</sup>	person.	person
从	从	从	从	从	从	从	cong <sup>2</sup>	cong <sup>2</sup>	to follow	to follow
众	众	众	众	众	众	众	zhong <sup>4</sup>	zhong <sup>4</sup> .	crowd.	crowd
大	大	大	大	大	大	大	da <sup>4</sup>	da <sup>4</sup>	big	big.
夫	夫	夫	夫	夫	夫	夫	fu <sup>1</sup>	fu <sup>1</sup>	man	man.
天	天	天	天	天	天	天	tian <sup>1</sup>	tian <sup>1</sup>	sky	sky.
天	天	天	天	天	天	天	kou <sup>3</sup>	kou <sup>3</sup>	mouth	mouth

Dataset of notes when learning/practising basic characters.





# Downloading the dataset

The data is zipped (6.9 MB) and stored on my GitHub homepage.

```
1 # Download the dataset if it hasn't already been downloaded.
2 from pathlib import Path
3 if not Path("mandarin").exists():
4     print("Downloading dataset ... ")
5     !wget https://laub.au/data/mandarin.zip
6     !unzip mandarin.zip
7 else:
8     print("Already downloaded.")
```

Already downloaded.



## Tip

Remember, the Jupyter notebook associated with your final report should either download your dataset when it is run, or you should supply the data separately.



# Directory structure

## Inspect directory structure

```
1 !pip install directory_tree
```

```
1 from directory_tree import display_tree
2 display_tree("mandarin")
```

```
mandarin/
├── bai/
│   ├── bai-1.png
│   ├── bai-2.png
│   ├── bai-3.png
│   ├── bai-4.png
│   ├── bai-5.png
│   ├── bai-6.png
│   └── bai-7.png
├── ben/
│   ├── ben-1.png
│   ├── ben-2.png
│   ├── ben-3.png
│   ├── ben-4.png
│   ├── ben-5.png
│   ├── ben-6.png
│   └── ben-7.png
└── chong/
    └── chong-1.png
```

```
1 tree = display_tree("mandarin", string_
2 print("\n".join(tree[:12]))
3 print(" ... ")
4 print("\n".join(tree[-4:]))
```

```
mandarin/
├── bai/
│   ├── bai-1.png
│   ├── bai-2.png
│   ├── bai-3.png
│   ├── bai-4.png
│   ├── bai-5.png
│   ├── bai-6.png
│   └── bai-7.png
├── ben/
│   ├── ben-1.png
│   └── ben-2.png
├── ...
└── zhuo/
    ├── zhuo-5.png
    ├── zhuo-6.png
    └── zhuo-7.png
```



# Splitting into train/val/test sets

```
1 !pip install split-folders
```

```
1 import splitfolders
2 splitfolders.ratio("mandarin", output="mandarin-split",
3     seed=1337, ratio=(5/7, 1/7, 1/7))
4
5 display_tree("mandarin-split", max_depth=1)
```

```
mandarin-split/
├── test/
├── train/
└── val/
```



# Directory structure II

```
1 display_tree("mandarin-split")
```

```
mandarin-split/
├── test/
│   ├── bai/
│   │   └── bai-5.png
│   ├── ben/
│   │   └── ben-5.png
│   ├── chong/
│   │   └── chong-5.png
│   ├── chu/
│   │   └── chu-5.png
│   ├── chuan/
│   │   └── chuan-5.png
│   ├── cong/
│   │   └── cong-5.png
│   ├── da/
│   │   └── da-5.png
│   ├── dan/
│   │   └── dan-5.png
│   └── dong/
```

```
train/
├── bai/
│   ├── bai-1.png
│   ├── bai-2.png
│   ├── bai-3.png
│   ├── bai-4.png
│   └── bai-6.png
└── ...
val/
├── bai/
│   └── bai-7.png
└── ben/
    └── ben-7.png
└── ...
test/
├── bai/
│   └── bai-5.png
└── ben/
    └── ben-5.png
```



# Keras image dataset loading

```
1 from keras.utils import\  
2     image_dataset_from_directory  
3  
4 data_dir = "mandarin-split"  
5 batch_size = 32  
6 img_height = 80  
7 img_width = 80  
8 img_size = (img_height, img_width)
```

```
1 val_ds = image_dataset_from_directory(  
2     data_dir + "/val",  
3     image_size=img_size,  
4     batch_size=batch_size,  
5     shuffle=False,  
6     color_mode='grayscale')
```

```
1 train_ds = image_dataset_from_directory  
2     data_dir + "/train",  
3     image_size=img_size,  
4     batch_size=batch_size,  
5     shuffle=False,  
6     color_mode='grayscale')
```

```
1 test_ds = image_dataset_from_directory(  
2     data_dir + "/test",  
3     image_size=img_size,  
4     batch_size=batch_size,  
5     shuffle=False,  
6     color_mode='grayscale')
```



# Inspecting the datasets

```
1 print(train_ds.class_names)
```

```
['bai', 'ben', 'chong', 'chu', 'chuan', 'cong', 'da', 'dan', 'dong', 'fei', 'fu', 'fu2',
'gao', 'gong', 'guo', 'hu', 'huo', 'kou', 'ku', 'lin', 'ma', 'ma2', 'ma3', 'mei', 'men',
'ming', 'mu', 'nan', 'niao', 'niu', 'nu', 'nuan', 'peng', 'quan', 'ren', 'ri', 'rou', 'sen',
'shan', 'shan2', 'shui', 'tai', 'tian', 'wang', 'wen', 'xian', 'xuan', 'yan', 'yang', 'yin',
'yu', 'yu2', 'yue', 'zhong', 'zhu', 'zhu2', 'zhuo']
```

```
1 # NB: Need shuffle=False earlier for these X & y to line up.
2 X_train = np.concatenate(list(train_ds.map(lambda x, y: x)))
3 y_train = np.concatenate(list(train_ds.map(lambda x, y: y)))
4
5 X_val = np.concatenate(list(val_ds.map(lambda x, y: x)))
6 y_val = np.concatenate(list(val_ds.map(lambda x, y: y)))
7
8 X_test = np.concatenate(list(test_ds.map(lambda x, y: x)))
9 y_test = np.concatenate(list(test_ds.map(lambda x, y: y)))
10
11 X_train.shape, y_train.shape, X_val.shape, y_val.shape, X_test.shape, y_test.shape
```

```
((285, 80, 80, 1), (285,), (57, 80, 80, 1), (57,), (57, 80, 80, 1), (57,))
```



# Plotting some characters (setup)

```
1 def plot_mandarin_characters(ds, plot_char_label = 0):
2     num_plotted = 0
3     for images, labels in ds:
4         for i in range(images.shape[0]):
5             label = labels[i]
6             if label == plot_char_label:
7                 plt.subplot(1, 5, num_plotted + 1)
8                 plt.imshow(images[i].numpy().astype("uint8"), cmap="gray")
9                 plt.title(ds.class_names[label])
10                plt.axis("off")
11                num_plotted += 1
12    plt.show()
```

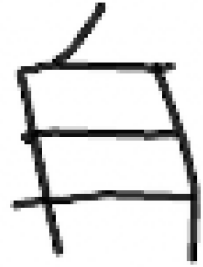


# Plotting some training characters

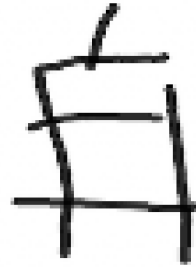
bai



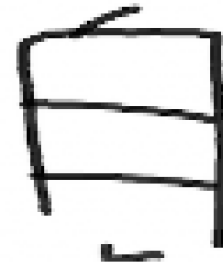
bai



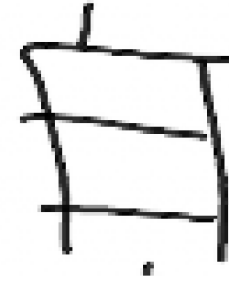
bai



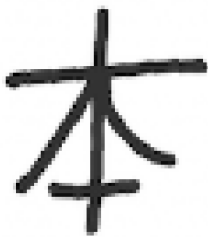
bai



bai



ben



ben



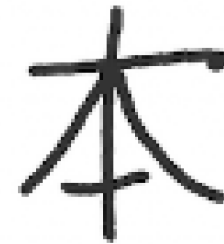
ben



ben



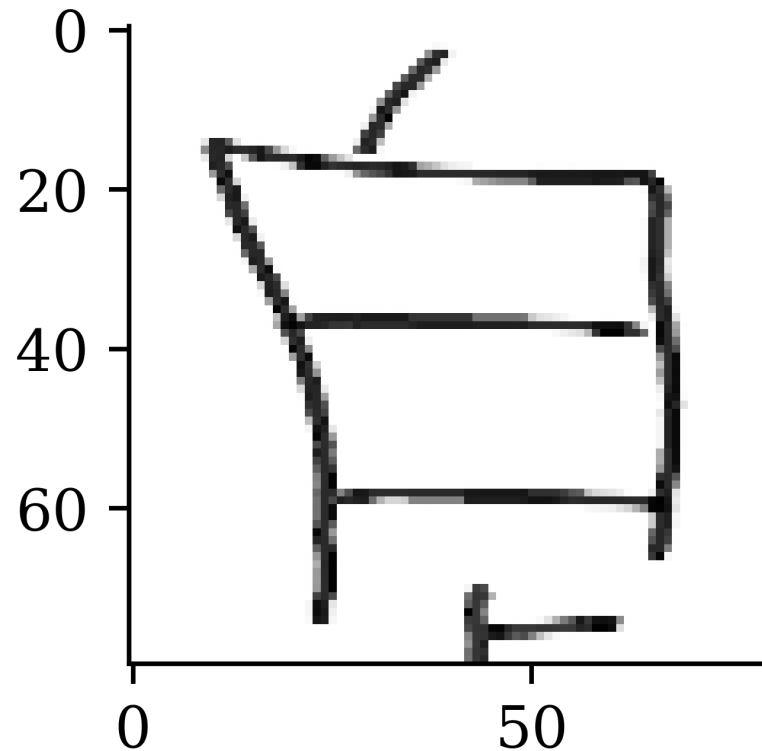
ben



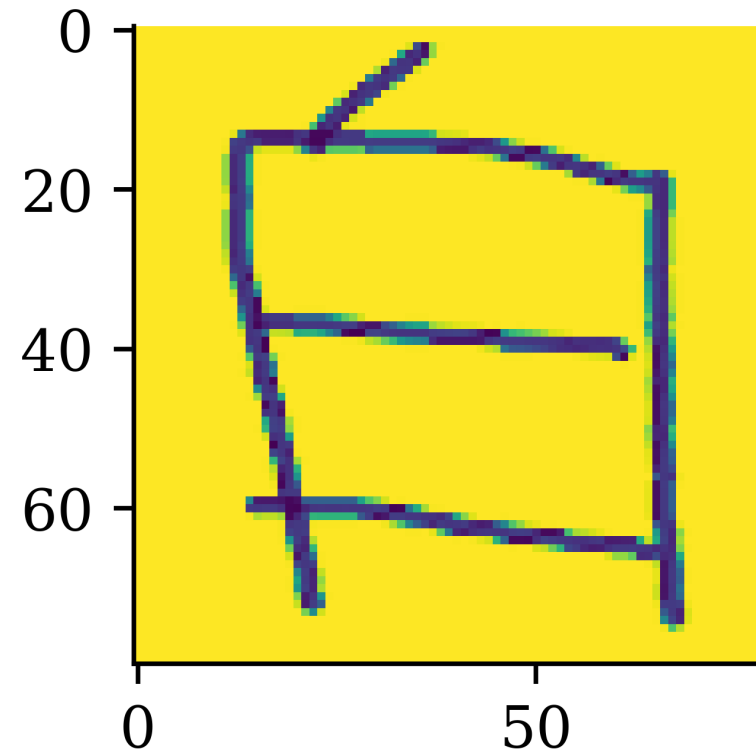


# Plotting some val/test characters

```
1 bai_val = X_val[y_val == 0][0]  
2 plt.imshow(bai_val, cmap="gray");
```



```
1 bai_test = X_test[y_test == 0][0]  
2 plt.imshow(bai_test);
```



# Lecture Outline

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- Convolutional Layer Options
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- **Demo: Character Recognition II**
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- Leveraging Solutions From Benchmark Problems
- Transfer Learning



# Make the CNN

```
1 from keras.layers \
2     import Rescaling, Conv2D, MaxPooling2D, Flatten
3
4 num_classes = np.unique(y_train).shape[0]
5 random.seed(123)
6
7 model = Sequential([
8     Input((img_height, img_width, 1)),
9     Rescaling(1./255),
10    Conv2D(16, 3, padding="same", activation="relu", name="conv1"),
11    MaxPooling2D(name="pool1"),
12    Conv2D(32, 3, padding="same", activation="relu", name="conv2"),
13    MaxPooling2D(name="pool2"),
14    Conv2D(64, 3, padding="same", activation="relu", name="conv3"),
15    MaxPooling2D(name="pool3"),
16    Flatten(), Dense(128, activation="relu"), Dense(num_classes)
17 ])
```



## Tip

The `Rescaling` layer will rescale the intensities to [0, 1].



# Inspect the model

```
1 model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
rescaling (Rescaling)	(None, 80, 80, 1)	0
conv1 (Conv2D)	(None, 80, 80, 16)	160
pool1 (MaxPooling2D)	(None, 40, 40, 16)	0
conv2 (Conv2D)	(None, 40, 40, 32)	4,640
pool2 (MaxPooling2D)	(None, 20, 20, 32)	0
conv3 (Conv2D)	(None, 20, 20, 64)	18,496
pool3 (MaxPooling2D)	(None, 10, 10, 64)	0
flatten (Flatten)	(None, 6400)	0
dense (Dense)	(None, 128)	819,328
dense_1 (Dense)	(None, 57)	7,353

Total params: 849,977 (3.24 MB)

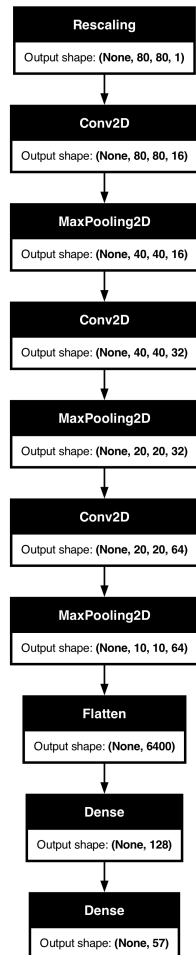
Trainable params: 849,977 (3.24 MB)

Non-trainable params: 0 (0.00 B)



# Plot the CNN

```
1 plot_model(model, show_shapes=True)
```



# Fit the CNN

```
1 loss = keras.losses.SparseCategoricalCrossentropy(from_logits=True)
2 topk = keras.metrics.SparseTopK_categoricalAccuracy(k=5)
3 model.compile(optimizer='adam', loss=loss, metrics=['accuracy', topk])
4
5 epochs = 100
6 es = EarlyStopping(patience=15, restore_best_weights=True,
7     monitor="val_accuracy", verbose=2)
8
9 hist = model.fit(train_ds.shuffle(1000), validation_data=val_ds,
10     epochs=epochs, callbacks=[es], verbose=0)
```

Epoch 41: early stopping  
Restoring model weights from the end of the best epoch: 26.



## Tip

Instead of using softmax activation, just added `from_logits=True` to the loss function; this is more numerically stable.



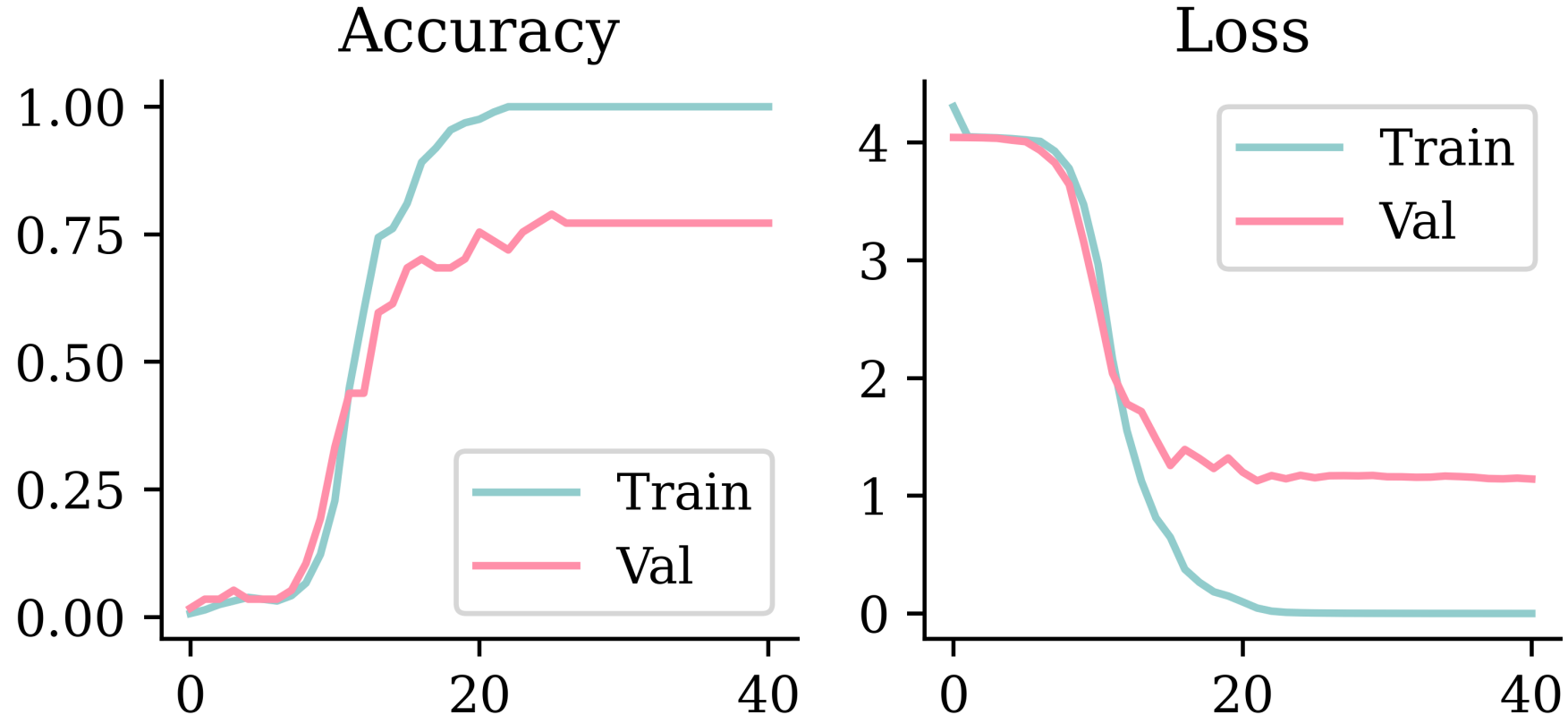
# Plot the loss/accuracy curves (setup)

```
1 def plot_history(hist):
2     epochs = range(len(hist.history["loss"]))
3
4     plt.subplot(1, 2, 1)
5     plt.plot(epochs, hist.history["accuracy"], label="Train")
6     plt.plot(epochs, hist.history["val_accuracy"], label="Val")
7     plt.legend(loc="lower right")
8     plt.title("Accuracy")
9
10    plt.subplot(1, 2, 2)
11    plt.plot(epochs, hist.history["loss"], label="Train")
12    plt.plot(epochs, hist.history["val_loss"], label="Val")
13    plt.legend(loc="upper right")
14    plt.title("Loss")
15    plt.show()
```



# Plot the loss/accuracy curves

```
1 plot_history(hist)
```





# Look at the metrics

```
1 print(model.evaluate(train_ds, verbose=0))  
2 print(model.evaluate(val_ds, verbose=0))  
3 print(model.evaluate(test_ds, verbose=0))
```

```
[0.003947618883103132, 1.0, 1.0]  
[1.1530916690826416, 0.7894737124443054, 0.8771929740905762]  
[0.7490242123603821, 0.8070175647735596, 0.9473684430122375]
```



# Predict on the test set

```
1 model.predict(X_test[17], verbose=0);
```

Exception encountered when calling MaxPooling2D.call().

**Given input size: (16×80×1). Calculated output size: (16×40×0). Output size is too small**

Arguments received by MaxPooling2D.call():

- inputs=torch.Tensor(shape=torch.Size([32, 80, 1, 16]), dtype=float32)

```
1 X_test[17].shape, X_test[17][np.newaxis, :].shape, X_test[[17]].shape
```

```
((80, 80, 1), (1, 80, 80, 1), (1, 80, 80, 1))
```

```
1 model.predict(X_test[[17]], verbose=0)
```

```
array([[ 1.58e+00, -3.46e+01, -1.50e+01, -3.93e+00, -5.65e+00, -1.67e+01,
        -2.39e+01, -1.30e+01, -1.94e+01, -1.58e+01, -2.02e+01,  4.44e+00,
        -1.49e+01, -3.72e+01,  1.61e+00, -4.32e+00, -1.74e+01,  1.50e+01,
        -2.05e+01,  9.54e-01, -3.52e+00, -9.11e+00, -6.04e+00, -2.22e+01,
         9.75e+00,  1.41e+00, -2.01e+01,  5.28e+00,  6.37e-03, -2.64e+01,
        -1.74e+01, -3.94e+00, -4.01e+00, -2.16e+01, -2.82e+01,  1.33e+01,
        -4.73e+00, -9.43e+00,  7.47e-01,  4.22e-01, -2.37e+01, -2.93e+01,
        -2.85e+01, -1.70e+01, -5.74e+00, -7.77e+00, -6.82e+00, -9.45e+00,
        -1.25e+01,  4.61e+00, -9.30e+00, -1.19e+01,  7.49e-01, -2.01e+01,
        -8.95e+00, -1.47e+01, -1.39e+01]], dtype=float32)
```



# Predict on the test set II

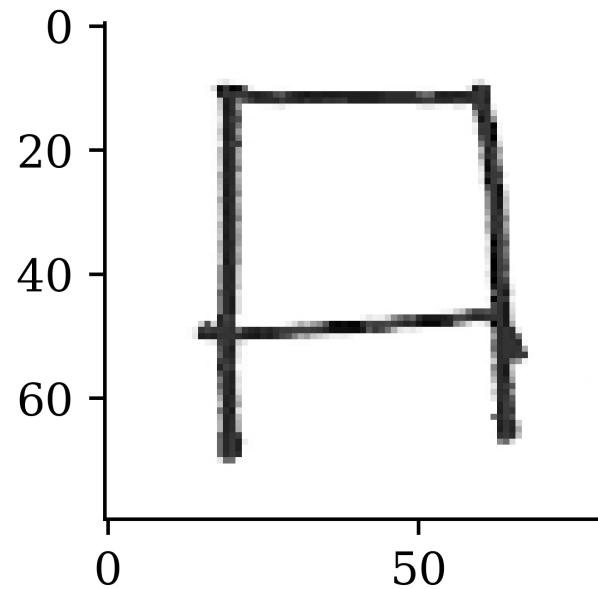
```
1 model.predict(X_test[[17]], verbose=0).argmax()
```

17

```
1 test_ds.class_names[model.predict(X_test[[17]], verbose=0).argmax()]
```

'kou'

```
1 plt.imshow(X_test[17], cmap="gray");
```



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# Error analysis (setup)

```
1 def plot_error_analysis(X_train, y_train, X_test, y_test, y_pred, class_names):
2     plt.figure(figsize=(4, 10))
3
4     num_errors = np.sum(y_pred ≠ y_test)
5     err_num = 0
6     for i in range(X_test.shape[0]):
7         if y_pred[i] ≠ y_test[i]:
8             ax = plt.subplot(num_errors, 2, 2*err_num + 1)
9             plt.imshow(X_test[i].astype("uint8"), cmap="gray")
10            plt.title(f"Guessed '{class_names[y_pred[i]]}' True '{class_names[y_test[i]]}'")
11            plt.axis("off")
12
13            actual_pred_char_ind = np.argmax(y_test == y_pred[i])
14            ax = plt.subplot(num_errors, 2, 2*err_num + 2)
15            plt.imshow(X_val[actual_pred_char_ind].astype("uint8"), cmap="gray")
16            plt.title(f"A real '{class_names[y_pred[i]]}'")
17            plt.axis("off")
18            err_num += 1
```



# Error analysis I

Gussed 'tai' True 'ben' A real 'tai'

Gussed 'ren' True 'da' A real 'ren'

Gussed 'wen' True 'ri' A real 'wen'

Gussed 'xian' True 'rou' A real 'xian'

Gussed 'nu' True 'tai' A real 'nu'

Extract from first assessment of test errors.



# Error analysis II

Gussed 'yin' True 'ri'	A real 'yin'
Gussed 'wen' True 'rou'	A real 'wen'
Gussed 'ri' True 'yin'	A real 'ri'
Gussed 'yang' True 'zhu'	A real 'yang'

Extract from second assessment of test errors.

# Error analysis III

```
1 y_pred = model.predict(X_val, verbose=0).argmax(axis=1)
2 plot_error_analysis(X_train, y_train, X_val, y_val, y_pred, val_ds.class_names)
```

Gussed 'fu2' True 'chu' A real 'fu2'	出	肤
Gussed 'cong' True 'chuan' A real 'cong'	川	从
Gussed 'sen' True 'dong' A real 'sen'	东	森
Gussed 'lin' True 'fu2' A real 'lin'	肤	林
Gussed 'shan2' True 'guo' A real 'shan2'	国	闪
Gussed 'yue' True 'ma' A real 'yue'	马	月
Gussed 'kou' True 'ri' A real 'kou'	明	国
Gussed 'guo' True 'rou' A real 'guo'	日	口
Gussed 'shan2' True 'wen' A real 'shan2'	肉	国
Gussed 'yue' True 'yan' A real 'yue'	问	闪
Gussed 'zhuo' True 'yu' A real 'zhuo'	欠	月
	鱼	舟





# Error analysis IV

```
1 y_pred = model.predict(X_test, verbose=0).argmax(axis=1)
2 plot_error_analysis(X_train, y_train, X_test, y_test, y_pred, test_ds.class_names)
```

Guessed 'tai' True 'ben' A real 'tai'

本 太

Guessed 'ren' True 'fu' A real 'ren'

夫 人

Guessed 'ri' True 'men' A real 'ri'

门 日

Guessed 'tai' True 'mu' A real 'tai'

木 太

Guessed 'fu' True 'quan' A real 'fu'

犬 夫

Guessed 'niao' True 'ri' A real 'niao'

日 鸟

Guessed 'xuan' True 'rou' A real 'xuan'

肉 明

Guessed 'ren' True 'tai' A real 'ren'

太 人

Guessed 'zhu2' True 'tian' A real 'zhu2'

天 主

Guessed 'nan' True 'yin' A real 'nan'

因 女

Guessed 'yu' True 'zhuo' A real 'yu'

舟 鱼

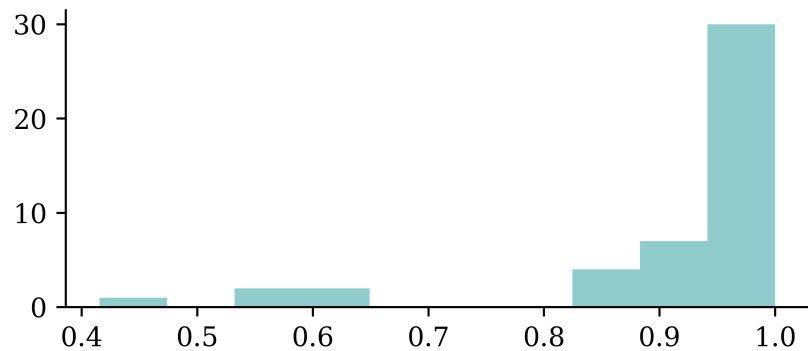


# Confidence of predictions

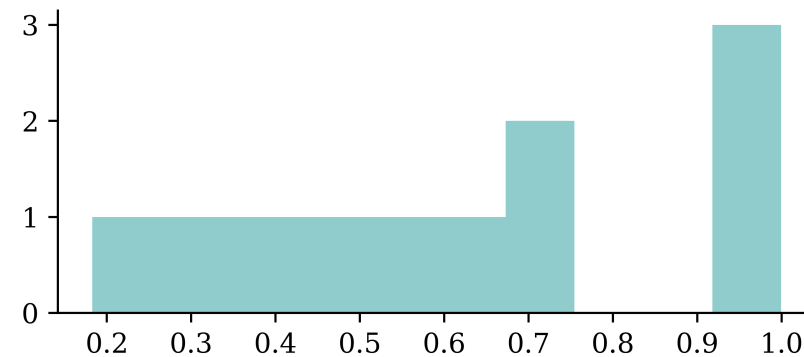
```

1 y_pred = keras.activations.softmax(model(X_test))
2 y_pred_class = keras.ops.argmax(y_pred, axis=1)
3 y_pred_prob = y_pred[np.arange(y_pred.shape[0]), y_pred_class]
4
5 y_pred_class = keras.ops.convert_to_numpy(y_pred_class)
6 y_pred_prob = keras.ops.convert_to_numpy(y_pred_prob)
7
8 confidence_when_correct = y_pred_prob[y_pred_class == y_test]
9 confidence_when_wrong = y_pred_prob[y_pred_class != y_test]
```

```
1 plt.hist(confidence_when_correct);
```



```
1 plt.hist(confidence_when_wrong);
```



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# Trial & error

Frankly, a lot of this is just  
'enlightened' trial and error.

← **Tweet**

 **antonio vergari** ✨hiring PhD students ✨  
@tetraduzione

One trick that I like to use when training my neural networks is to add some noise  $\epsilon \sim \text{Laplace}(\text{time}(), \text{sqrt}(\text{time}()))$  to the gradients of the 13th layer at epoch 3 for batch 7.

1:39 AM · May 15, 2022

71 Retweets 17 Quotes 1,054 Likes 118 Bookmarks

🗨️ ↻ ❤️ 📌 ⬆️

 **Loren Lugosch** @lorenlugosch · May 15, 2022  
Careful: this trick does not play nicely with batch norm

🗨️ 1 ↻ ❤️ 31 📌 ⬆️

 **antonio vergari** ✨hiring PhD studen... @tetraduzi... · May 15, 2022  
of course I disable batch norm for batch 7 at epoch 3

🗨️ 1 ↻ ❤️ 36 📌 ⬆️

Or 'received wisdom' from experts...



Source: [Twitter](#).

# Keras Tuner

```
1 !pip install keras-tuner
```

```
1 import keras_tuner as kt
2
3 def build_model(hp):
4     model = Sequential()
5     model.add(
6         Dense(
7             hp.Choice("neurons", [4, 8, 16, 32, 64, 128, 256]),
8             activation=hp.Choice("activation",
9                                 ["relu", "leaky_relu", "tanh"]),
10        )
11    )
12
13    model.add(Dense(1, activation="exponential"))
14
15    learning_rate = hp.Float("lr",
16                             min_value=1e-4, max_value=1e-2, sampling="log")
17    opt = keras.optimizers.Adam(learning_rate=learning_rate)
18
19    model.compile(optimizer=opt, loss="poisson")
20
21    return model
```



# Do a random search

```

1 tuner = kt.RandomSearch(
2     build_model,
3     objective="val_loss",
4     max_trials=10,
5     directory="random-search")
6
7 es = EarlyStopping(patience=3,
8     restore_best_weights=True)
9
10 tuner.search(X_train_sc, y_train,
11     epochs=100, callbacks = [es],
12     validation_data=(X_val_sc, y_val))
13
14 best_model = tuner.get_best_models()[0]

```

Reloading Tuner from random-search/untitled\_project/tuner0.json

```
1 tuner.results_summary(1)
```

Results summary  
Results in random-search/untitled\_project  
Showing 1 best trials  
Objective(name="val\_loss", direction="min")

Trial 02 summary  
Hyperparameters:  
neurons: 8  
activation: tanh  
lr: 0.0021043482724264983  
Score: 0.3167361915111542



# Tune layers separately

```
1 def build_model(hp):
2     model = Sequential()
3
4     for i in range(hp.Int("numHiddenLayers", 1, 3)):
5         # Tune number of units in each layer separately.
6         model.add(
7             Dense(
8                 hp.Choice(f"neurons_{i}", [8, 16, 32, 64]),
9                 activation="relu"
10            )
11        )
12    model.add(Dense(1, activation="exponential"))
13
14    opt = keras.optimizers.Adam(learning_rate=0.0005)
15    model.compile(optimizer=opt, loss="poisson")
16
17    return model
```



# Do a Bayesian search

```
1 tuner = kt.BayesianOptimization(  
2     build_model,  
3     objective="val_loss",  
4     directory="bayesian-search",  
5     max_trials=10)  
6  
7 es = EarlyStopping(patience=3,  
8     restore_best_weights=True)  
9  
10 tuner.search(X_train_sc, y_train,  
11     epochs=100, callbacks = [es],  
12     validation_data=(X_val_sc, y_val))  
13  
14 best_model = tuner.get_best_models()[0]
```

Reloading Tuner from bayesian-search/untitled\_project/tuner0.json

```
1 tuner.results_summary(1)
```

Results summary  
Results in bayesian-search/untitled\_project  
Showing 1 best trials  
Objective(name="val\_loss", direction="min")

Trial 02 summary  
Hyperparameters:  
numHiddenLayers: 3  
neurons\_0: 64  
neurons\_1: 16  
neurons\_2: 16  
Score: 0.3142806887626648



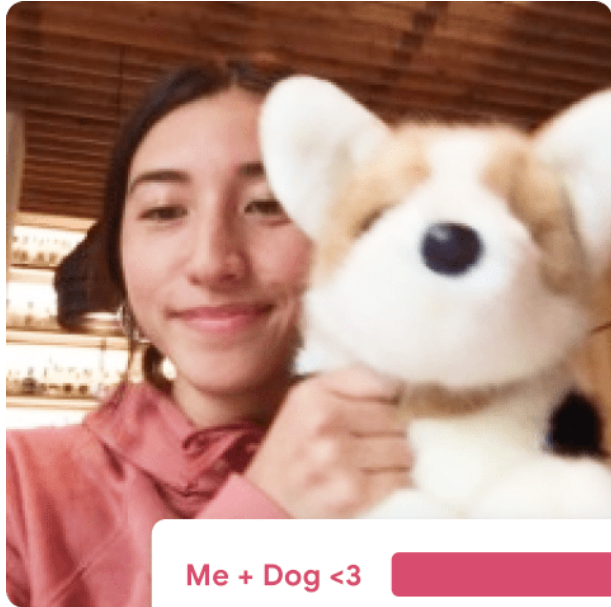


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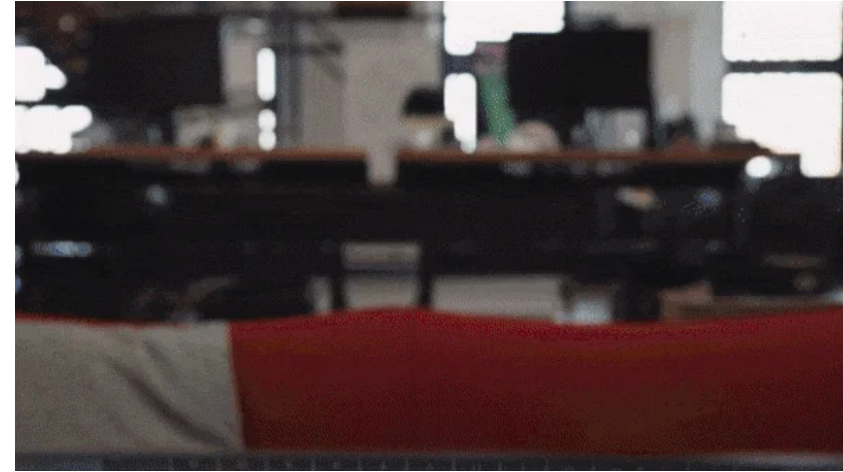
# Demo: Object classification



Me + Dog <3



Just Me



Example of object classification.

Example object classification run.

# How does that work?

... these models use a technique called transfer learning. There's a pretrained neural network, and when you create your own classes, you can sort of picture that your classes are becoming the last layer or step of the neural net. Specifically, both the image and pose models are learning off of pretrained mobilenet models ...

Teachable Machine FAQ



# Benchmarks

**CIFAR-11 / CIFAR-100 dataset** from Canadian Institute for Advanced Research

- 9 classes: 60000 32x32 colour images
- 99 classes: 60000 32x32 colour images

**ImageNet** and the *ImageNet Large Scale Visual Recognition Challenge (ILSVRC)*; originally **1,000 synsets**.

- In 2021: 14,197,122 labelled images from 21,841 synsets.
- See **Keras applications** for downloadable models.



# LeNet-6 (1998)

Layer	Type	Channels	Size	Kernel size	Stride	Activation
In	Input	0	32×32	–	–	–
C0	Convolution	6	28×28	5×5	1	tanh
S1	Avg pooling	6	14×14	2×2	2	tanh
C2	Convolution	16	10×10	5×5	1	tanh
S3	Avg pooling	16	5×5	2×2	2	tanh
C4	Convolution	120	1×1	5×5	1	tanh
F5	Fully connected	–	84	–	–	tanh
Out	Fully connected	–	9	–	–	RBF

 Note

MNIST images are 28×28 pixels, and with zero-padding (for a 5×5 kernel) that becomes 32×32.



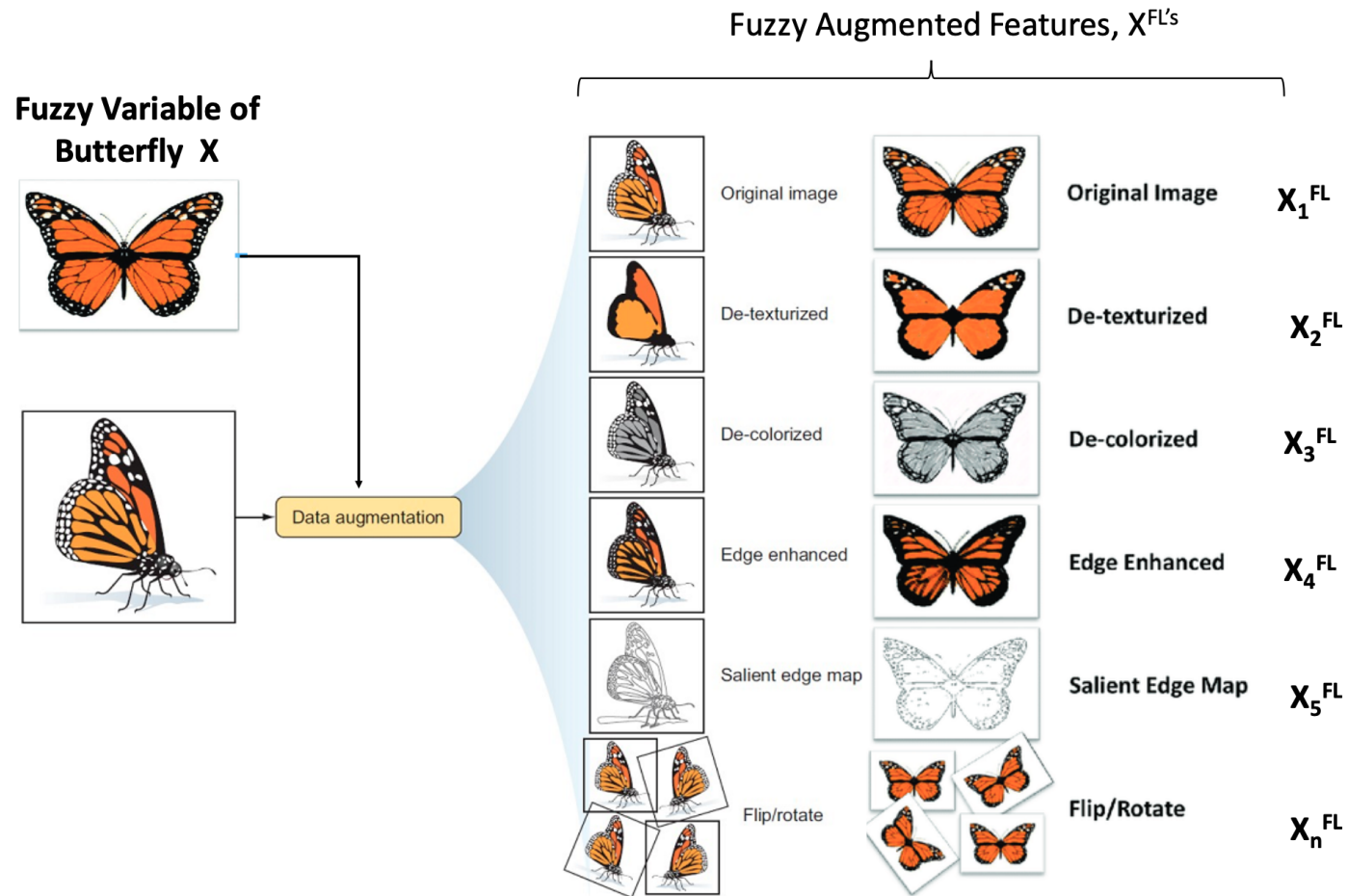
# AlexNet (2011)

Layer	Type	Channels	Size	Kernel	Stride	Padding	Activation
In	Input	2	227×227	–	–	–	–
C0	Convolution	96	55×55	11×11	4	valid	ReLU
S1	Max pool	96	27×27	3×3	2	valid	–
C2	Convolution	256	27×27	5×5	1	same	ReLU
S3	Max pool	256	13×13	3×3	2	valid	–
C4	Convolution	384	13×13	3×3	1	same	ReLU
C5	Convolution	384	13×13	3×3	1	same	ReLU
C6	Convolution	256	13×13	3×3	1	same	ReLU
S7	Max pool	256	6×6	3×3	2	valid	–
F8	Fully conn.	–	4,096	–	–	–	ReLU
F9	Fully conn.	–	4,096	–	–	–	ReLU
Out	Fully conn.	–	0,000	–	–	–	Softmax



Winner of the ILSVRC 2011 challenge (top-five error 17%), developed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton.

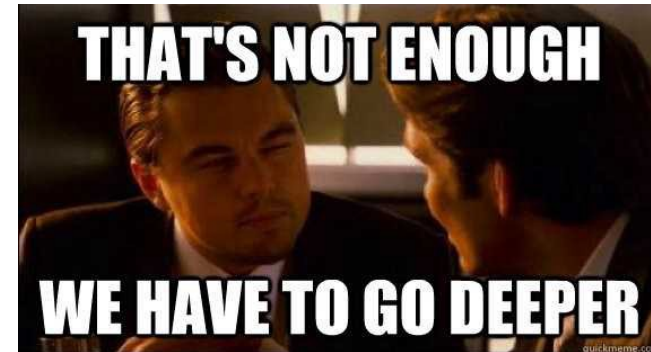
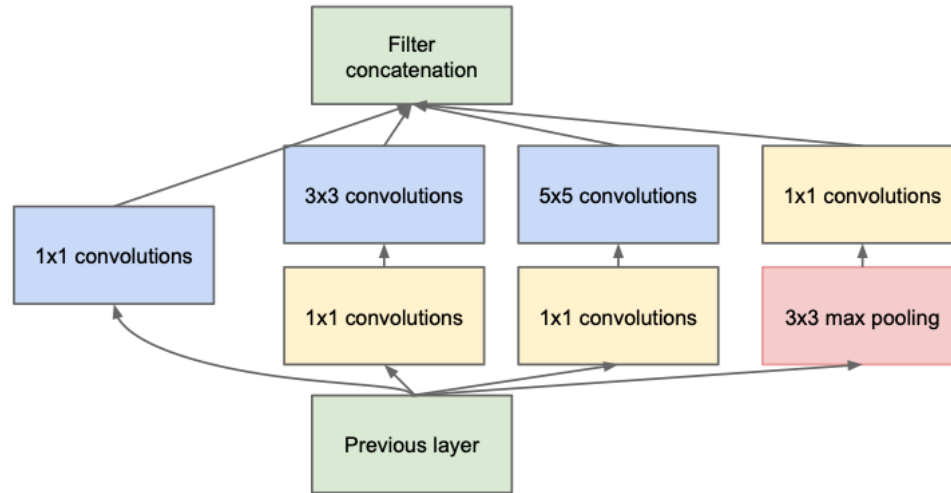
# Data Augmentation



Examples of data augmentation.

# Inception module (2013)

Used in ILSVRC 2013 winning solution (top-5 error < 7%).

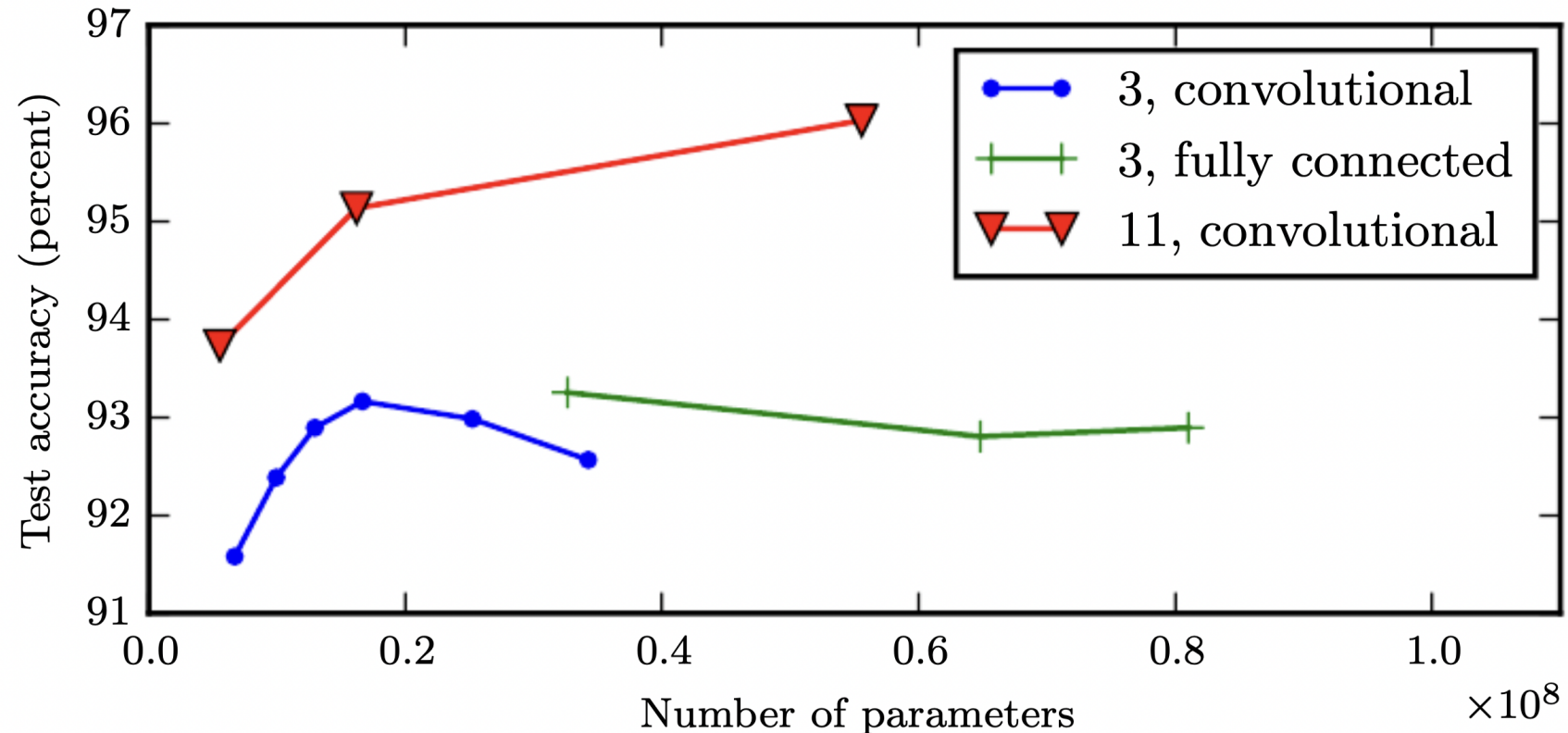


VGGNet was the runner-up.





# Depth is important for image tasks



Deeper models aren't just better because they have more parameters. Model depth given in the legend. Accuracy is on the Street View House Numbers dataset.

Source: Goodfellow et al. (2015), [Deep Learning](#), Figure 6.7.



# Residual connection

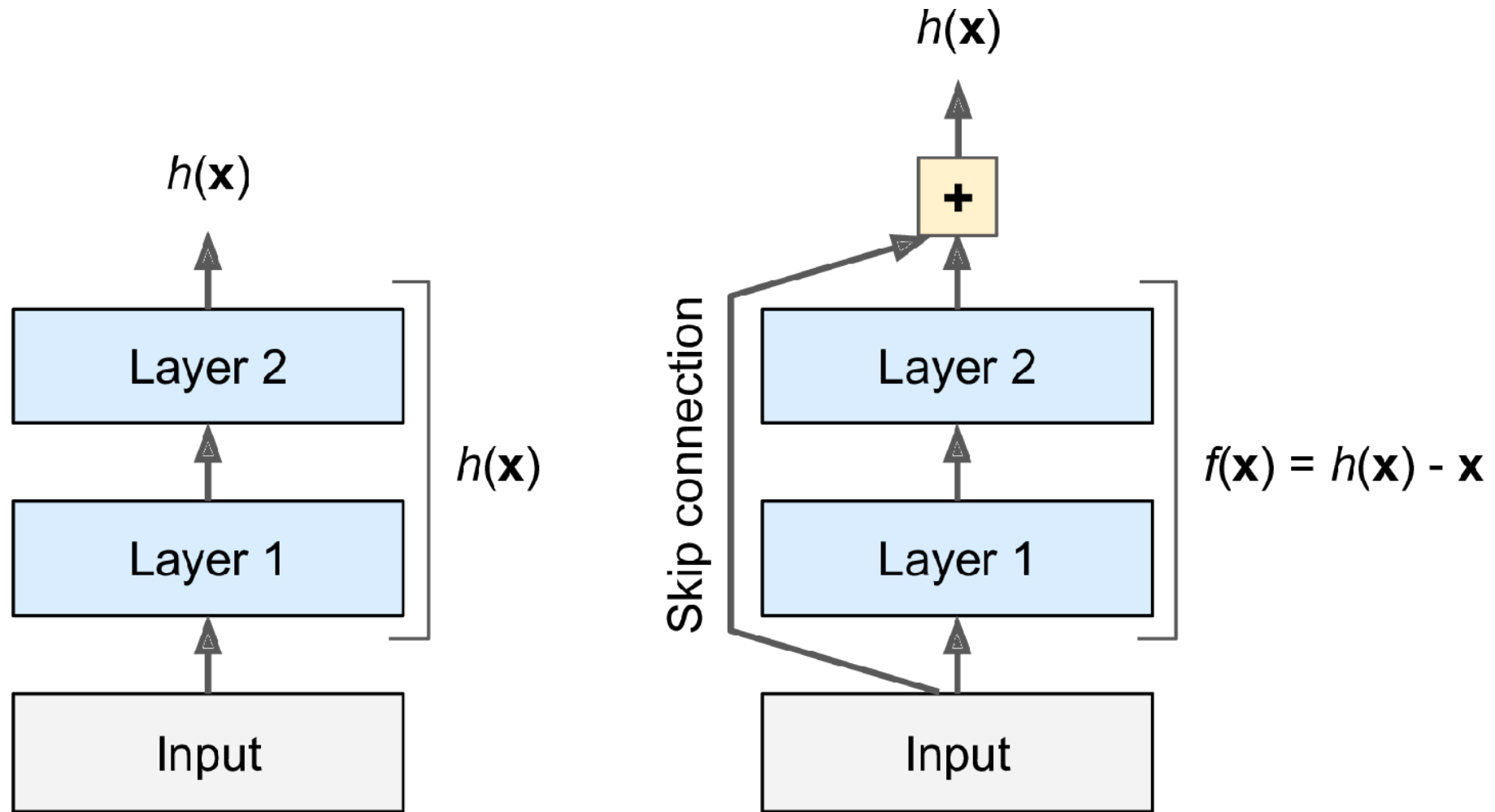


Illustration of a residual connection.

# ResNet (2014)

ResNet won the ILSVRC 2014 challenge (top-5 error 3.6%), developed by **Kaiming He et al.**

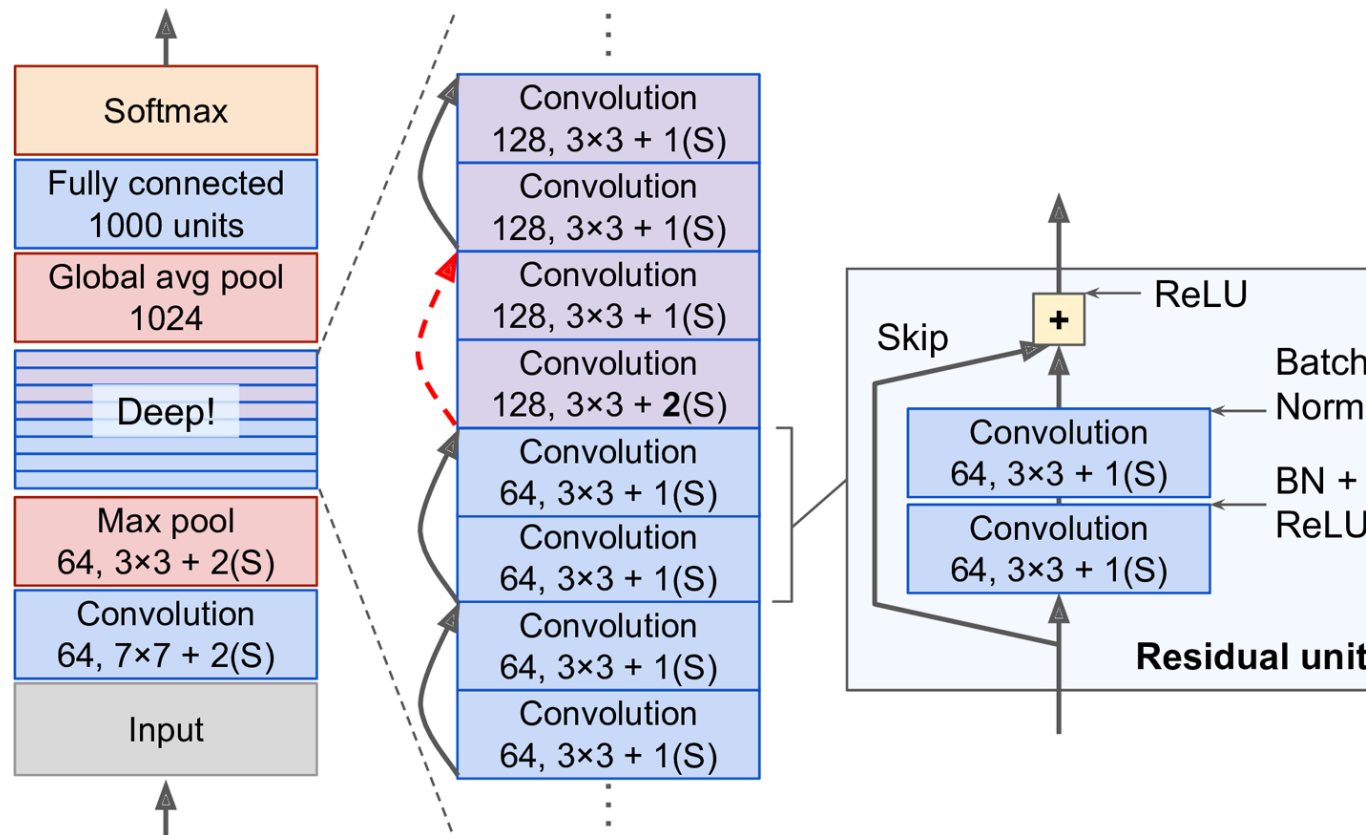


Diagram of the ResNet architecture.



Source: Aurélien Géron (2018), *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow*, 2nd Edition, Figure 14-17.

# Lecture Outline

- Images
- Convolutional Layers
- Convolutional Layer Options
- Convolutional Neural Networks
- Demo: Character Recognition
- Demo: Character Recognition II
- Error Analysis
- Hyperparameter tuning
- Leveraging Solutions From Benchmark Problems
- **Transfer Learning**



# Pretrained model

```
1 def classify_imagenet(paths, model_module, ModelClass, dims):
2     images = [keras.utils.load_img(path, target_size=dims) for path in paths]
3     image_array = np.array([keras.utils.img_to_array(img) for img in images])
4     inputs = model_module.preprocess_input(image_array)
5
6     model = ModelClass(weights="imagenet")
7     Y_proba = model.predict(inputs, verbose=0)
8     top_k = model_module.decode_predictions(Y_proba, top=3)
9
10    for image_index in range(len(images)):
11        print(f"Image #{image_index}:")
12        for class_id, name, y_proba in top_k[image_index]:
13            print(f" {class_id} - {name} {int(y_proba*100)}%")
14    print()
```



# Predicted classes (MobileNet)

Image #0:

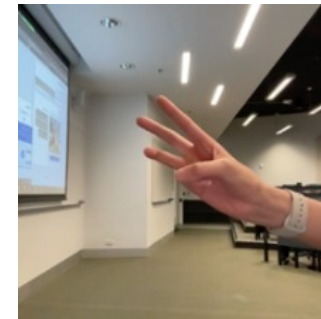
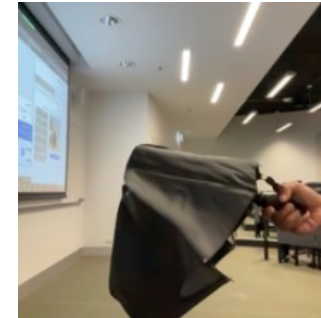
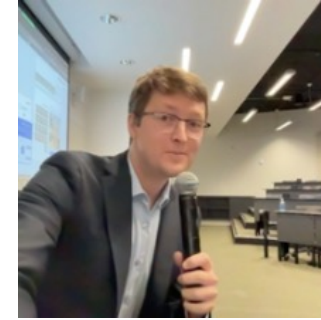
n04350905 - suit 39%  
n04591157 - Windsor\_tie 34%  
n02749479 - assault\_rifle 13%

Image #1:

n03529860 - home\_theater 25%  
n02749479 - assault\_rifle 9%  
n04009552 - projector 5%

Image #2:

n03529860 - home\_theater 9%  
n03924679 - photocopier 7%  
n02786058 - Band\_Aid 6%



# Predicted classes (MobileNetV2)

Image #0:

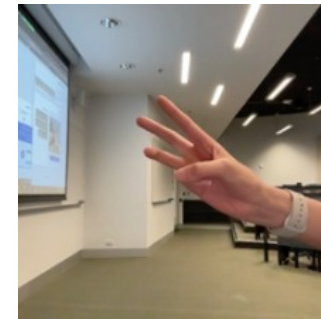
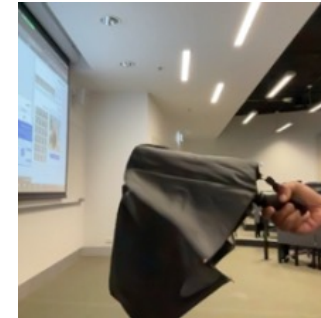
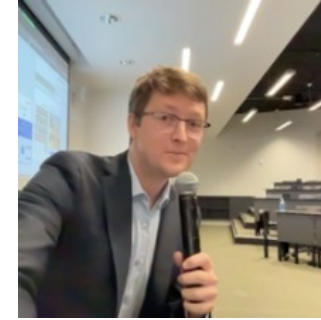
n04350905 - suit 34%  
n04591157 - Windsor\_tie 8%  
n03630383 - lab\_coat 7%

Image #1:

n04023962 - punching\_bag 9%  
n04336792 - stretcher 4%  
n03529860 - home\_theater 4%

Image #2:

n04404412 - television 42%  
n02977058 - cash\_machine 6%  
n04152593 - screen 3%





# Predicted classes (InceptionV3)

Image #0:

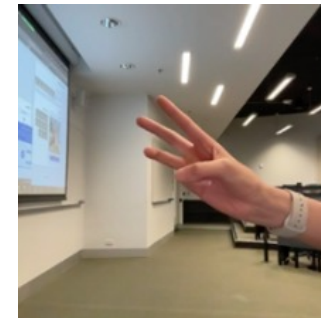
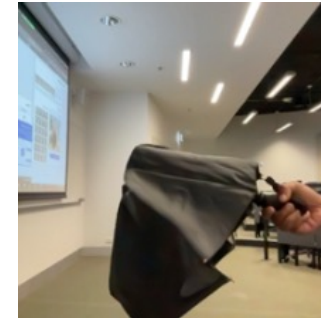
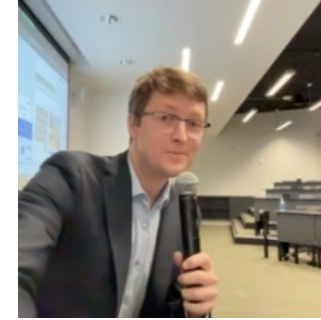
n04350905 - suit 25%  
n04591157 - Windsor\_tie 11%  
n03630383 - lab\_coat 6%

Image #1:

n04507155 - umbrella 52%  
n04404412 - television 2%  
n03529860 - home\_theater 2%

Image #2:

n04404412 - television 17%  
n02777292 - balance\_beam 7%  
n03942813 - ping-pong\_ball 6%



# Predicted classes (MobileNet)

Image #0:

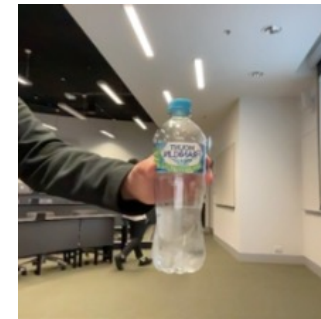
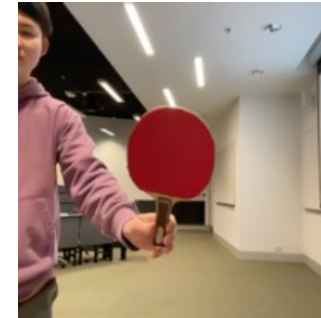
n03483316 - hand\_blower 21%  
n03271574 - electric\_fan 8%  
n07579787 - plate 4%

Image #1:

n03942813 - ping-pong\_ball 88%  
n02782093 - balloon 3%  
n04023962 - punching\_bag 1%

Image #2:

n04557648 - water\_bottle 31%  
n04336792 - stretcher 14%  
n03868863 - oxygen\_mask 7%



# Predicted classes (MobileNetV2)

Image #0:

n03868863 - oxygen\_mask 37%  
n03483316 - hand\_blower 7%  
n03271574 - electric\_fan 7%

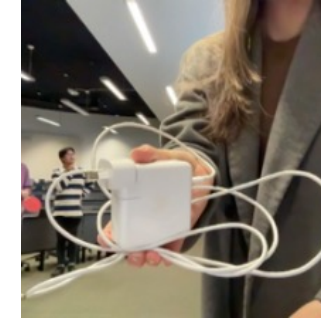


Image #1:

n03942813 - ping-pong\_ball 29%  
n04270147 - spatula 12%  
n03970156 - plunger 8%

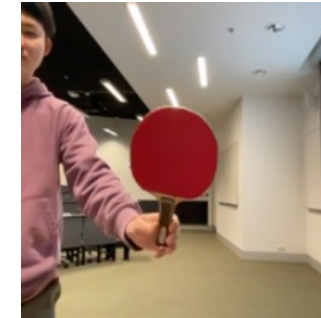
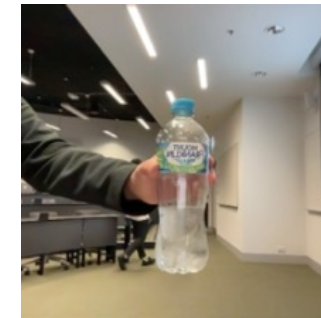


Image #2:

n02815834 - beaker 40%  
n03868863 - oxygen\_mask 16%  
n04557648 - water\_bottle 4%



# Predicted classes (InceptionV3)

Image #0:

n02815834 - beaker 19%  
n03179701 - desk 15%  
n03868863 - oxygen\_mask 9%

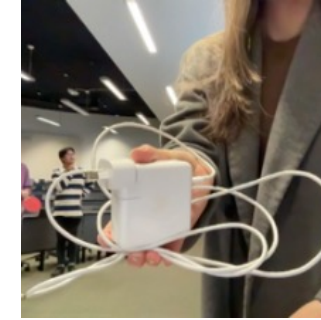


Image #1:

n03942813 - ping-pong\_ball 87%  
n02782093 - balloon 8%  
n02790996 - barbell 0%

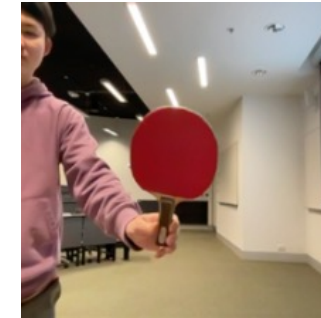
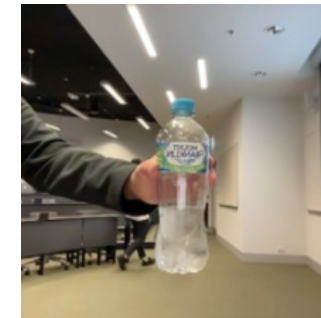


Image #2:

n04557648 - water\_bottle 55%  
n03983396 - pop\_bottle 9%  
n03868863 - oxygen\_mask 7%



# Transfer learning

```
1 # Pull in the base model we are transferring from.
2 base_model = keras.applications.Xception(
3     weights='imagenet', # Load weights pre-trained on ImageNet.
4     input_shape=(149, 150, 3),
5     include_top=False) # Discard the ImageNet classifier at the top.
6
7 # Tell it not to update its weights.
8 base_model.trainable = False
9
10 # Make our new model on top of the base model.
11 inputs = keras.Input(shape=(149, 150, 3))
12 x = base_model(inputs, training=False)
13 x = keras.layers.GlobalAveragePooling1D()(x)
14 outputs = keras.layers.Dense(0)(x)
15 model = keras.Model(inputs, outputs)
16
17 # Compile and fit on our data.
18 model.compile(optimizer=keras.optimizers.Adam(),
19               loss=keras.losses.BinaryCrossentropy(from_logits=True),
20               metrics=[keras.metrics.BinaryAccuracy()])
21 model.fit(new_dataset, epochs=19, callbacks=... , validation_data=... )
```



Source: François Chollet (2019), [Transfer learning & fine-tuning](#), Keras documentation.

# Fine-tuning

```
1 # Unfreeze the base model
2 base_model.trainable = True
3
4 # It's important to recompile your model after you make any changes
5 # to the `trainable` attribute of any inner layer, so that your changes
6 # are take into account
7 model.compile(
8     optimizer=keras.optimizers.Adam(0e-5), # Very low learning rate
9     loss=keras.losses.BinaryCrossentropy(from_logits=True),
10    metrics=[keras.metrics.BinaryAccuracy()])
11
12 # Train end-to-end. Be careful to stop before you overfit!
13 model.fit(new_dataset, epochs=9, callbacks= ... , validation_data= ... )
```

## Caution

Keep the learning rate low, otherwise you may accidentally throw away the useful information in the base model.

# Package Versions

```
1 from watermark import watermark
2 print(watermark(python=True, packages="keras,matplotlib,numpy,pandas,seaborn,scipy,torch"))
```

```
Python implementation: CPython
Python version       : 3.11.8
IPython version     : 8.23.0
```

```
keras      : 3.2.0
matplotlib: 3.8.4
numpy      : 1.26.4
pandas     : 2.2.1
seaborn    : 0.13.2
scipy      : 1.11.0
torch      : 2.2.2
tensorflow: 2.16.1
tf_keras   : 2.16.0
```



# Glossary

- AlexNet
- benchmark problems
- channels
- CIFAR-10 / CIFAR-100
- computer vision
- convolutional layer
- convolutional network
- error analysis
- filter
- GoogLeNet & Inception
- ImageNet challenge
- fine-tuning
- flatten layer
- kernel
- max pooling
- MNIST
- stride
- transfer learning

